Technological Standardization, Endogenous Productivity and Transitory Dynamics

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Abstract

We propose the use of technological standardization as a novel indicator of technological change. Standardization is an important feature of technological progress in many industries and triggers the adoption of new or drastically improved technologies. Our new indicator allows us to identify technology shocks and analyze their impact on the cycle, but also enables us to investigate the cyclical nature of technology adoption. *First*, our results suggest that not only inventive activity, but more importantly the actual adoption of new technologies is endogenous to the cycle. Technology is thus not a purely exogenous phenomenon. *Second*, the identified technology shock diffuses slowly and the positive reaction of output and investment is S-shaped as is typical of technological diffusion. Before picking up permanently, total factor productivity temporarily decreases as the newly adopted technology is incompatible with installed physical, human and organizational capital. *Third*, we find that standardization is an essential mechanism for anchoring expectations about future movements of macroeconomic aggregates as evidenced by the positive and immediate reaction of stock market data to a technology shock.

JEL-Classification: E32, O31, O33
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1 Introduction

Despite a very long and on-going debate, technology remains a popular explanation for business cycle fluctuations. However, the perception of technology in a macroeconomic context is still a nebulous concept which differs from its more literal interpretation as it is understood outside of macroeconomics. Business cycle economists — in contrast to endogenous growth theories — have made less use of the insights from the industrial organization literature on technology adoption. However, a thorough understanding of the role of technology is necessary given that a large strand of the business cycle literature still relies heavily upon exogenous technology shocks as a driver of short-run fluctuations.

This paper seeks to analyze empirically the impact of technology on productivity and to gain more insight into the feedback mechanism between innovation and the macroeconomic cycle. Using extensive technological data and a new micro-founded indicator of technological change, namely technological standardization, we study the effect of technology shocks on macroeconomic aggregates — a question which still figures on the research agenda of macroeconomists due to the difficulty of identifying technology shocks. We will argue that our proposed indicator precedes the coordinated adoption of new technologies and anchors expectations about future technological progress by reducing uncertainty and ensuring technological homogeneity. Using a direct, micro-level indicator of technological progress allows us to look into the specific channels that lead to technological change. We therefore not only look at the impact of technology on productivity and the cycle, but also analyze the extent to which technology is cycle-driven. We employ data for the US economy.

To measure technology adoption, we propose to use data on standardization. Technological standards are comparable to patents in that they are documents which describe the technical features of innovations and technologies. Prominent examples of standards are electricity plugs, Internet protocols or mobile phone standards such as the 1G, 2G or 3G standard families. However, in contrast to patents which have been shown to be poor indicators of technological change, standards are economically and technologically highly meaningful, because they reflect the actual adoption (instead of invention) of an innovation and *trigger* technological diffusion. Standardization is above all an important feature of the ICT sector due to its key role in harmonizing technological devices and ensuring compatibility. ICT has been shown to be a general purpose technology (Basu and Fernald, 2008) which is why we use ICT standards for our empirical analysis. We are therefore identifying a *specific* technology shock which is interpreted as one of radical technical change. Technical change that is rather incremental or happens at the plant level such as organizational restructuring or managerial innovation is not the focus of our analysis. Although we are concentrating on ICT, our aim is to uncover general mechanisms that are characteristic of technological diffusion. The fact that ICT has constituted *the* dominant technology in recent decades motivates our approach.

The seminal papers of Kydland and Prescott (1982) and Long and Plosser (1983) developed the concept of stochastic technological change as an exogenous driver of business cycles. Despite the criticism that challenged the Real Business Cycle (RBC) hypothesis, the idea of technology being a decisive factor for business cycle fluctuations has not lost its attractiveness. More recently, models have increasingly relied on shocks to the marginal efficiency of investment as defined by Greenwood *et al.* (1988). These investment-specific technology (IST) shocks are more often directly associated with technological change taken

literally as they only affect *new* vintages of capital.[1] It thus requires investment in new machinery and human capital to realize technical progress. The concept of "vintage capital" is used in particular for models which stress that technological change is *embodied* and leads to technological obsolescence and economic depreciation (as opposed to physical depreciation).[2] The approach taken in this paper follows this notion of technology.

The recent literature on "news shocks" (Beaudry and Portier, 2006; Jaimovich and Rebelo, 2009) has contributed to the revival of the idea that technology, or more precisely news about future technological improvements, drive business cycles. Anticipated improvements in total factor productivity lead to business cycle fluctuations despite the fact that the shock only materializes after several lags. The "news shock" literature relates to the present paper since the generated dynamics can be similar to the ones triggered by technological progress which is characterized by long diffusion lags. The implications of slow technology diffusion pose macroeconometric challenges which require the use of meaningful information about technology adoption (Lippi and Reichlin, 1993; Leeper *et al.*, 2011). Tracking technological diffusion on the aggregate, however, has proven challenging territory. A large and lively debate has therefore concentrated on the correct identification of technology shocks deduced from macroeconomic data.

In contrast, we attempt to explain technology as a phenomenon itself instead of considering technology as a simple exogenous force. A natural framework for such complex interactions is a vector autoregression (VAR) approach. In this paper, we specifically adapt our VAR model to the context of slow technology diffusion by opting for a generous and variable-specific lag length. In particular, we use a Bayesian VAR framework which allows us to deal with overparameterization by introducing a differentiated lag structure that captures the importance of distant technology lags for the dynamics of the system.

Our findings can be be grouped into three major points. *First*, we investigate if technology is indeed exogenous as often assumed in macroeconomics. We find that technology adoption is actually cycle-driven and relate this finding to the importance of economic incentives (demand effects) and liquidity constraints in the light of high adoption costs. *Second*, we find that standardization is an important driver for output and investment in equipment and software as well as for long-run productivity. This result confirms our interpretation of standardization as an indicator of technological progress. In particular, we find that disembodied productivity (TFP) decreases following a shock to embodied technology due to the incompatibility of new and old vintages of capital. The positive effect on productivity only materializes after years. *Third*, we find that our identified shocks communicate information to economic agents about future productivity in the spirit of Beaudry and Portier (2006). Standardization triggers the diffusion of technologies; although this diffusion process is very lengthy and characterized by S-shaped diffusion patterns, forward-looking variables like stock market indices pick up this information on impact.

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[1]Greenwood *et al.* (1997) show that IST shocks can be either thought of as lowering the cost of investment (and thus increasing the quantity of new investment goods) or improving the productivity, and thus quality, of new investment. Using industry-level data, Boddy and Gort (1974) do indeed show that productivity changes can for the most part be traced back to changes in embodied technology. A similar point is made by Greenwood *et al.* (1997, 2000) who show that more than 60% of long-term productivity growth and 30% of short-term fluctuations are driven by investment-specific technological change. Fisher (2006) analyzes theoretically and empirically the quantitative effects of neutral and investment-specific technology shocks on business cycle fluctuations. He finds that the latter is the larger driver of volatility.

[2]See Cooley *et al.* (1997) for a discussion on the concept of economic depreciation.

The next section motivates and discusses the relevance of our new measure of technological change. A review of the literature follows in section 3. Section 4 and 5 describe the data and the econometric methodology. Section 6 presents the results and their interpretation while section 7 investigates the robustness of the results. Finally, Section 8 concludes.

2 Tracking technological progress

2.1 Technological diffusion and information

Technology shocks are often assumed to appear out of nowhere which is why productivity is modelled as an exogenous process in many macroeconomic papers. However, endogenous growth theories and the innovation economics literature draw a very different picture: technology is not uncoupled from what is happening in the economy, but is very much an *economic* phenomenon.

Figure 1 displays a more complex, admittedly very stylized, picture of the interaction between the macroeconomic cycle on the one hand and technology from its invention to commercialization on the other hand. Innovative inputs in the form of R&D constitute the starting point of a new technology. R&D is itself procyclical (Barlevy, 2007; Ouyang, 2011). A random science flow, which could be interpreted as scientific luck or findings from fundamental research pursued in universities and academia, acts as an exogenous force. The innovative output of R&D and science is partly patented. The time lag between initial R&D expenditures and the arrival of a new technology is considerable and can take up to several decades.[3]

The existence of different new technologies does not necessarily mean that each one is actually used by firms and consumers. On the contrary, many potentially useful inventions coexist without (yet) being marketed. Standardization plays a very important role in this process as it selects one technology among competing ones. Once a technology is selected, uncertainty is reduced and complementary investment into the new technology picks up. Standardization is thus a trigger of technology adoption. However, standardization itself can be expected to be a function of the cycle as it is very costly to commit to a new technology.

A large body of literature starting with the classical example of Griliches (1957) has shown that technology diffuses slowly. The effect of the newly standardized technology on the cycle only materializes after considerable delay as adoption rates follow an S-shaped pattern. For the econometrician, slow diffusion is a challenging problem as it can lead to non-fundamental VAR representations (Lippi and Reichlin, 1993, 1994).[4]

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[3]This is why it is hard to capture technology shocks using data on R&D expenditures.

[4]Consider a Wold representation for Y_t: $Y_t = D(L)u_t$ where $D(L)$ is a lag polynomial. This moving average representation is not unique as shown by Hansen and Sargent (1991). *First*, one can obtain an observationally equivalent representation by finding a matrix which maps the reduced-form errors into structural ones: $Y_t = D(L)CC^{-1}u_t = \tilde{D}(L)\varepsilon_t$. Defining the structural shocks as $\varepsilon_t = C^{-1}u_t$ and the propagation matrix as $\tilde{D}(L) = D(L)C$, the above transformation is concerned with the well-known problem of *identification*. Knowledge or assumptions about the structure of the matrix C, motivated by economic theory, helps recovering the structural shocks. A second form of non-uniqueness, non-fundamentalness, is hardly ever discussed in empirical applications of structural vector autoregressions, but is as important

Non-fundamentalness arises whenever the *information* spanned by the structural shocks is larger than the space covered by the available data. News shocks, anticipation of shocks and slow diffusion are prominent examples of non-fundamental representations.[5] Potentially, the econometrician identifies shocks which are actually moving averages of the fundamental innovations. In a nutshell, there are two ways to solve the non-fundamentalness problem. The first one consists in modelling information flows directly which involves making very strong assumptions about time lags and functional forms of diffusion processes or the way news shocks materialize. The second one is about using direct measures of news or diffusion which is the approach taken in this paper.

Essentially, we try to align the *information set* of the econometrician with the one of the agents by using a measure which coincides with the point in time when the technology is adopted or its future adoption is announced. Standardization represents the impulse when economic agents first receive meaningful signals about the adoption of a new technology and thus adjust their behaviour accordingly. Standardization is the trigger of technology diffusion. The actual commercialization and the subsequent use of the new technology in production processes then generates a feedback on the macroeconomic cycle.

2.2 Existing indicators of technological progress

The empirical identification of technology shocks thus constitutes a, if not *the*, major challenge in the RBC literature.[6] The macroeconomic literature on technology shocks has mainly worked with long-run restrictions to identify productivity shocks following the seminal work of Galí (1999). Identification is indirect by postulating how technology shocks should behave in the long-run and by assuming that the common stochastic trend found in macroeconomic variables represents exclusively permanent technology shocks (King *et al.*, 1991). The analysis of short-run effects is however flawed if the assumption is violated and technology is not the only variable affecting productivity in the long-run.

Another means of identifying technological change from macroeconomic data is to use corrected measures of Solow residuals: Basu *et al.* (2006) adjust raw measures of total factor productivity (TFP) for capacity utilization, increasing returns, imperfect competition and aggregation effects. This approach, however, suffers from the assumption that once residuals are adjusted for non-technological factors, the remaining technology component is considered purely exogenous. As will be shown later, cycle-driven technology adoption seriously challenges this conjecture.

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as identification. In this case, knowing Y_t is not enough to recover ε_t. Formally speaking, a VAR representation is fundamental if its structural shocks can be recovered from *past* and *current* observations of Y_t. This is the case when the moving-average representation is invertible.

[5] Lippi and Reichlin (1993, 1994) show that S-shaped diffusion curves, as they are typical for patterns of technology adoption, can lead to non-fundamental representations unless the diffusion process is assumed to have a certain functional form. Non-fundamentalness can as well arise in other contexts that are similar to technological diffusions. The macroeconometric literature has also considered models with foresight (Leeper *et al.*, 2011) and news shocks (Fève *et al.*, 2009; Fève and Jidoud, 2012; Leeper and Walker, 2011). News shocks in particular are often associated with technological progress.

[6] The correct identification of technology shocks is of such relevance since macroeconomists have been trying to identify the effect of technology shocks on the economy as a whole and in particular on factor inputs. Even if technology shocks have only a small impact on the cycle, the question remains nevertheless an important one: whether factor inputs react positively or contract is respectively interpreted as a proof for the RBC paradigm or as an indication for the validity of sticky-price models of the New-Keynesian type.

To address the problem that long-run restrictions might capture not only technology, but also non-technological factors, more direct measures of technological change can be used. All these indicators have in common that they consider technological change to be embodied. One the one hand, a vast literature relies on R&D and patent data to capture direct indicators of *inventive* activity (Shea, 1998; Kogan *et al.*, 2012). On the other hand, proxies for the *adoption* of technological innovations have been used. The work which this paper probably relates to most closely is Alexopoulos (2011) who relies on technology publications, i.e. manuals and user guides, as a measure for technology adoption.

The measures described above display several advantageous features, but are also plagued by some shortcomings. Patent counts and data on R&D expenditures represent innovative activity and therefore directly measure technological change. However, R&D expenditures and patent counts often tell little about the economic significance of an innovation and are only indirectly related to the introduction of new technologies. R&D expenditures measure the input, but not the output of inventive activity, and patent counts measure inventions and not the actual implementation of a new technology.

Indicators such as technology publications (Alexopoulos, 2011) are variables which measure exclusively innovations that are actually commercialized and thus capture economically significant innovations. More importantly, these are temporally close to the actual date of adoption of a new technology. Nevertheless, these indicators measure phenomena that are *symptoms* of technology adoption, but might neglect the important anticipation effects when technologies diffuse slowly. As a consequence, non-fundamentalness might arise in VAR representations as described above. This might impede a thorough understanding of the mechanisms and dynamics of technological progress.

Our indicator of technology adoption shares the merits of the above technology indicators, but surmounts their shortcomings. Standards are explicit measures of innovation and are directly linked to technology adoption. Standardization data allow for the analysis of rich dynamics and mechanisms leading to the implementation of new technologies. Due to the high economic and technical content of standards, we are able to investigate the effects of technology on aggregate macroeconomic variables. Standardization is directly connected to innovative activity on the micro-level and has the advantage of being a trigger of the actual implementation of new technologies. In particular, we use data from the information and communications technology (ICT) sector. As shown by Basu and Fernald (2008), this industry has been found to be the main driver of productivity growth in recent decades due to its nature as a general purpose technology (GPT).

2.3 A new measure of technological progress: Standardization

Definition and practicalities of standardization

Standards play an important role in the everyday life of all industrialized societies. Prominent examples of standards are electricity plugs, paper size formats (i.e. A4 for most of the world and "letter" size in the US) or quality standards (i.e. ISO 9001:2008). A (technological) standard is essentially a document which pins down *how to do* certain things. A standard describes the required technical features of products and processes and is issued by standard setting organizations on the national and international level. Loosely speaking,

our series on standardization is comparable to patent data, but richer in terms of economic content and representative of technological *implementation*.

Standards are set in a number of different ways.[7] De facto standards are set by a market selection process where consumers prefer a certain technology over another, acquire it either by traditional use or due to the monopolistic supply of a unique technology. Especially in the latter case these standards are often proprietary. Examples of de facto standards are the QWERTY keyboard or Microsoft's Excel. Voluntary or informal standards are often set by industry organizations and comprise open standards which are mainly non-proprietary. An example is the standard setting activity of the Internet Engineering Task Force (IETF). Formal standards are imposed by national or international standard setting organizations and are binding regulations. Examples of standard setting organizations are the American National Standards Institute (ANSI), the European Telecommunications Standards Institute (ETSI) or the International Organization for Standardization (ISO).

Most standards are released in the fields of engineering technologies, information and telecommunications as well as materials technologies. Popular examples are the first generation (1G), second generation (2G) and third generation (3G) standards in the mobile phone industry. 1G technology describes a family of standards which defined analog mobile telecommunication systems as they were introduced in the early 1980's. The 2G family of mobile telecommunication standards replaced 1G technology by using digital signals and was introduced in the early 1990's. 3G technology allowed for high-speed data transmission and mobile Internet access and was effectively launched in the early 2000's.[8] In the following, we will discuss the advantages of standardization data for measuring technology adoption. We will demonstrate the properties of our indicator taking the mobile telecommunications sector as an example.

Economic implications of standardization

Compatibility, network effects and "lumpy" adoption. The adoption of many new technologies is subject to network effects; standardization is often essential to benefit from these positive externalities (Katz and Shapiro, 1985). Compatibility is a key issue for most technological applications such as ICT where the benefit from using a technology depends positively on the number of users. Due to technological complexity and the desire to achieve industry-wide compatibility, the participants of a specific industry often choose to adopt new technologies in a coordinated manner through standardization.[9] Judging by technological content, a standard is therefore more aggregated than a patent. The decision to adopt a technology can be timed very precisely by adopting firms and constitutes an intentional *economic* decision. It is therefore only a logical consequence that technological standardization is characterized by discrete jumps. Moreover, many inventions are comprised in one standard and in turn many standards are adopted at the same time due to

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[7]See David and Greenstein (1990) for an overview of the different mechanisms that lead to the creation of a standard as well as the discussion in Gandal (2002).

[8]See Gandal *et al.* (2003) for a discussion of standard setting practices in Europe and North America for the mobile telecommunications sector.

[9]A relatively large literature in innovation economics addresses the importance of compatibility (standardization) for the adoption of technologies by producers and consumers (Katz and Shapiro, 1985, 1986; David and Greenstein, 1990; Farrell and Saloner, 1988).

network effects and technological interdependencies. Standardization constitutes therefore a channel of technology adoption which discretizes an otherwise smooth technology supply. Thus, adjustment to the technology frontier *has to* happen occasionally due to the very nature of technological progress. As we will show in section 4.2, standardization time series display exactly these stochastic properties of technology adoption. For our example of mobile telecommunications, the lack of compatibility between different analog 1G telecommunication systems motivated the European Commission to mandate a harmonized standard for 2G technologies in all member countries in order to facilitate roaming. When these standards were released, they represented many inventions and were linked to several other standards. For example, the standard families GSM and UMTS comprise over 1200 essential patents of a total of 72 firms (Bekkers and West, 2009).

Standardization as a selection mechanism which reduces uncertainty. A standard chooses one innovation among several co-existing innovations as the one that is to be applied by a whole industry and therefore lays the ground for the harmonization and compatibility of products and processes. Competing technologies are discarded. Rysman and Simcoe (2008) show that standardization is an important mechanism for an industry to *identify* relevant technologies and *promote* their use. For example, European legislators opted for the UMTS standard family among two competing rivals in order to push the development of 3G technologies. Via this selection mechanism, standards can reduce uncertainty substantially and define in which direction an industry is heading. Fontana *et al.* (2009) show for the case of wireless internet technology that standardization was essential for reducing uncertainty about competing technologies and therefore facilitated the subsequent commercialization and improvement of technological applications. The nature of standards as signalling mechanisms is closely linked to the literature on the role of news for macroeconomic fluctuations (Jaimovich and Rebelo, 2009; Beaudry and Portier, 2006).[10]

Discontinuous technologies and long-term impact. Once a standard is issued, firms adopt it (gradually) and thus replace old vintages of technology with a new one. In the spirit of the *radical vs. incremental innovation* dichotomy[11] found in the literature of innovation economics, we interpret our measure of technological change as one that captures radical and discontinuous technologies. This is motivated by the finding of Bekkers and Martinelli (2010) who show that standardization processes coincide with the creation of new technological opportunities and trajectories (Dosi, 1982). A *discontinuous* technological innovation is the starting point of a technological trajectory along which *continuous* innovations are constantly introduced until a new technological paradigm emerges. A standard defines a new technological basis which is often characterized by backwards non-compatibility. For instance, 2G is not compatible with 1G and neither is 3G compatible with 2G. This necessitated substantial, costly investment into interoperability and new infrastructure such as network towers. Standards "lock" an industry into a specific technology. The impact of such "QWERTY-nomics" (David, 1985) is substantial for future developments since network

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[10]As noted by Gandal *et al.* (2004) and Rysman and Simcoe (2008), standardization is an effective means of knowledge diffusion as participants are often required to disclose information on their intellectual property.

[11]See Garcia and Calantone (2002) for a discussion.

externalities, path dependence and irreversibility of investment make future technology a function of today's standardization choices.

3   Literature

Endogenous productivity

Papers studying the impact of innovative activity on macroeconomic variables often focus on long-run (growth) aspects, but neglect transitory dynamics and the impact on business cycles. While endogenous growth models endogenize technological progress as a decentral, cumulative process, RBC models typically assume a *stochastic* technology supply. However, it is not straightforward why technology should be more exogenous than any other component of the cycle. Furthermore, microeconomic analysis of R&D spending and patenting has consistently found that these measures are endogenous to macroeconomic variables.

The literature on R&D and patenting identifies three mechanisms that make innovative activity a function of the cycle: (1) economic incentives and demand effects, (2) the role of financing costs and (3) the opportunity cost hypothesis. *First*, demand effects such as the limited absorptive capacity of markets and profit-seeking can lead to innovative activity being procyclical (Geroski and Walters, 1995; Shleifer, 1986; Francois and Lloyd-Ellis, 2003). *Second*, financing costs might be an important factor for driving both innovation and adoption of new technologies and thus lead to procyclical technology. Ouyang (2011) shows that liquidity constraints are an important factor that drives procyclical R&D. Furthermore, such mechanisms should also play an important role for inventive output and commercialization.

Third, the opportunity cost hypothesis advocated by Aghion and Saint-Paul (1998) states that investment into R&D and organizational restructuring is more likely to happen during recessions as the opportunity costs of foregone profits are lower during downturns. As such, recession can have a "cleansing effect" (Caballero and Hammour, 1994). This theory advocates that technology should be countercyclical.[12] However, the different cyclical forces do not have to exclude each other. Barlevy (2007) shows that pro- and countercyclical channels can co-exist, but only the dominant effects — which are the procyclical forces in the case of R&D — will be visible in the aggregate data.[13]

Contrary to the literature on endogenous growth, the idea that productivity could be endogenous has only recently been introduced to business cycle analysis. Insights from the research programme initiated by Zvi Griliches and Edwin Mansfield on the economics of innovation and productivity growth have only slowly found their way into the field. It is especially the empirical finding that technology only diffuses slowly which has been introduced to business cycle models (see for example Rotemberg, 2003, for a first

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[12]Cooper and Haltiwanger (1993) show that machine replacement is concentrated during times of low labor productivity (such as summer months and recessions) when the replacement in terms of opportunity costs is low.

[13]Aghion *et al.* (2010) demonstrate that credit frictions can lead to procyclical long-term investment though it would be optimal to have countercyclicality if markets were complete. Aghion *et al.* (2012) and López-García *et al.* (2012) show that the countercyclicality of R&D as a result of opportunity costs can be reversed for those firms which are financially constrained.

contribution in this respect). Building on the literature about technology adoption, Comin and Gertler (2006) therefore endogenize productivity in a medium-term business cycle model with slow technology diffusion where R&D spending and expenditures for technology adoption vary procyclically.

Embodied technology and productivity dynamics

The importance of (embodied) technology for growth is well recognized in the economics profession; however, its effect on short-run fluctuations is not as clear cut. The short-run effect of technology is an issue which has mainly been tackled in the vintage capital literature which stresses the impact of embodied technological change on macroeconomic aggregates. One strand of this literature emphasizes the negative transitory effect on productivity due to learning as well as the incompatibility of new technologies with existing ones (Hornstein and Krusell, 1996; Cooley *et al.*, 1997; Greenwood and Yorukoglu, 1997; Andolfatto and MacDonald, 1998). The adoption of new technologies leads to short-run fluctuations of macroeconomic aggregates as resources are diverted to the reorganization of production and skill development in order to use new technologies efficiently. In particular, these models study the role of learning for the so-called "productivity paradox" in the light of the ICT revolution following Solow's diagnosis that "we can see the computer age everywhere but in the productivity statistics". Yorukoglu (1998) finds that the introduction of ICT requires a considerable investment into learning and stresses that it is in particular ICT capital which is characterized by a strong degree of incompatibility across different vintages. Samaniego (2006) stresses the need for reorganization at the plant level due to the incompatibility of new ICT technologies with existing expertise.

Standardization has started to become a popular topic in innovation economics, but — at least to our knowledge — its role in a macroeconomic context has so far not been looked at with the exception of Acemoglu *et al.* (2012) who examine its role for growth. The authors analyze the interactions between innovation, investment in learning related to new technologies and productivity growth in a theoretical framework. Standardization is defined as the diffusion process by which a new technology spreads through the economy and transforms innovations into embodied, usable technology. Innovation and standardization are thus complementary drivers of productivity growth.

Technological diffusion and "news"

Technology diffuses slowly and the initial shock only materializes with considerable delay. Nevertheless, technology shocks announce the arrival of the new direction in which an industry is heading. Expectations about future technological progress also play an important role for the investment in incremental innovation.[14] The seminal paper by Dosi (1982) stresses the importance of emerging "technological paradigms" as a stepping stone for further

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[14]Abernathy and Utterback (1978) and the subsequent literature on product life cycles (see Klepper, 1996 for a review) analyze regularities in the process of technological innovation. In this analysis, the development of radical innovations is characterized by rivalry between competing technologies and strong technological uncertainty. When a dominant design emerges, companies reduce their investment in competing technologies, and increasingly invest in incremental innovations building upon the dominant design.

technological progress. Product innovation is thus gradually replaced by process innovation. News signalling the emergence of a dominant design therefore serve as expectational anchors and encourage investment in new technologies which share a common technological basis.

Standards might therefore signal the arrival of a new "technological trajectory" (Bekkers and Martinelli, 2010). The role of signalling is not totally new to the business cycle literature. Beaudry and Portier (2006) use stock price movements to identify news about the future and show that these lead to an increase in TFP after several years. Consistent with the idea of long diffusion lags, these news shocks are interpreted by the authors as news about technological change which only materializes and leads to productivity increases after a long process of adoption. The theoretical counterpart of this idea is analyzed in Jaimovich and Rebelo (2009) who propose a model that includes news shocks which have an impact on productivity only in the future. Comin *et al.* (2009) model the idea of news shocks leading to changes in TFP by explicitly associating expectations about the future with fundamental technological changes in a model of endogenous technology adoption.

4   Description of the data

4.1   Data sources

The empirical identification of technology shocks is a crucial methodological challenge. In order to retrieve time series on standardization, we use the PERINORM database and collect formal standards which are released in the United States. PERINORM is a database intended for engineers which lists all formal standards which are released by different standard setting organizations. Time series are constructed by counting the number of standards which are released per quarter. The standard time series include all formal industry standards issued by American standardization bodies, such as ANSI, as well as international standard organizations issuing standards that apply to the US. In the basic specifications, we will work with the standard series from US standard setting organizations only, but will include the ones from international bodies later on. For a share of our standard counts, we only have information about the year, but not the month, of the release of the standard. We therefore adjust our final series by assuming the same quarterly distribution of these standards as for the one for which we have the complete date of release. Working with the standard series that only comprises standards where the complete date of release is available does not change our results. For some of the series, zero values are sporadically present at the beginning of the series which is why we add 1 to the standard series in order to be able to take logarithms.[15] We use data from the ICT sector for our econometric analysis, in particular the ICS (International Classification of Standards) classes 33 and 35. The former comprises telecommunications and the latter comprises information technology. Table 1 lists the different standard classes.

For the macroeconomic data, we employ time series from the NIPA tables from the Bureau of Economic Analysis (BEA), in particular non-residential investment in equipment and software, price indices for investment as well as consumption of goods and services.

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[15]When running the VAR using only those standard series that do not have zero values, results are the same independently of whether 1 is added or not.

We use data from the Bureau of Labor Statistics (BLS) such as output and hours worked in the business sector. Industrial production indices, data on capacity utilization as well as the Federal Funds rate are taken from the Board of Governors of the Federal Reserve (FRB). Our measure of TFP adjusted for capacity utilization is taken from John Fernald of the Federal Reserve Bank of San Francisco. Finally, we use the S&P 500 stock market and NASDAQ Composite indices. Data on macroeconomic aggregates are real, seasonally adjusted and transformed in per capita terms by dividing the series with the population aged 16 and above (taken from the BLS). All data are quarterly for the period 1975Q1–2010Q2. Detailed information on all the series used can be found in the appendix.

4.2 Cyclical patterns

In figure 2, we plot the untreated data for standards in both the ICT sector and for all ICS classes. The standard series is substantially "lumpier" than typical macroeconomic series at this frequency. The standard series display very low, or even negative, autocorrelations. This is due to the fact that standardization is a process characterized by clustering and discrete action. By the very nature of standardization, a quarter that is characterized by a high standardization rate will be followed by a low standardization rate in the next quarter. The standardization series is a pure flow variable and due to its microeconomic nature not subject to the same degree of aggregation as typical macroeconomic series. Figure 2 also shows that the standard series for ICT and for all ICS classes differ substantially despite the former being part of the latter.

One motivation for the analysis of the cyclical patterns of standardization is the fact that R&D and patenting have been found to be procyclical. In figure 3, we refer to this finding and plot the time series for R&D expenditures and ICT patent counts against output. A clear cyclical pattern emerges especially for the time period from 1985 on and thus strongly suggests that demand effects and liquidity costs might be important factors driving innovative input. Since standardization is a costly adoption process, we ask whether the results of the literature on R&D and patenting also carry over to technology adoption. We therefore explore the cyclical patterns of our new indicator and plot detrended non-farm business output as well as detrended and smoothed ICT standards[16] in figure 4 for the period 1975Q1 to 2010Q2. Clearly, the smoothed standard series shows a cyclical pattern which especially moves along with the cycle during recessions. The plot thus implies that standardization, and thus technology adoption, is procyclical.

Cross-correlations can give some information on the timing of this procyclicality. Figure 5 shows that both output and investment lead our smoothed standardization series by four quarters. The correlation coefficient of around 0.5 suggests that this effect might be even quite decisive. TFP adjusted for capacity utilization is lagging standardization by one quarter and is positively, but not very strongly correlated with standardization.

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[16]We detrend the standard series with a HP-filter and smooth the remaining high frequency movements since the standard series is very erratic. We do not apply a two-sided band-pass filter to the data as one would do for an erratic macroeconomic time series which is characterized by noise at high frequencies due to factors such as mismeasurement. In the case of our microeconomic standard series, however, discarding high frequency movements would be misleading as extreme values represent discrete technology adoption rather than mismeasurement. For the standardization data, we therefore smooth the detrended series using a simple moving average of window length of 5 quarters.

The procyclical feature of standardization as displayed in figures 4 and 5 could stem from three different explanations: (1) technology adoption has a positive impact on output, (2) technology adoption is procyclical as it is driven by the cycle or (3) causality runs in both directions: technology adoption is driven by the cycle but also generates a feedback on macroeconomic variables. The aim of this paper is to uncover exactly this circular feedback between the cycle and technology adoption. We will therefore investigate to what extent the patterns described here survive the test of more rigorous, structural analysis.

5   Econometric strategy

5.1   A Bayesian VAR which accounts for long diffusion lags

We are interested in the dynamic interaction between technology and the macroeconomic cycle and thus employ a vector autoregression model. Non-fundamentalness can arise in VAR models with news shocks or slow technology diffusion (Lippi and Reichlin, 1993; Leeper *et al.*, 2011). One solution to this non-fundamentalness problem is to align the information set of the econometrician with the one of the agents which is the approach taken in this paper. We decide to include 12 lags into the VAR — instead of the usual 4 lags that is often employed for quarterly data. The inclusion of a sufficient number of lags (as it is a prerequisite for any VAR) is necessary to capture the correct propagation dynamics, independent of the identification, but dependent on the timing at which one variable influences another.

Essentially this is an issue of unbiased estimation. The choice of a generous lag length is motivated by the observation that slow technology diffusion might require a larger number of lags in order to ensure the unbiased estimation of the VAR coefficients. This problem of "lag truncation bias" arises whenever the finite order VAR model is a poor approximation of the infinite order VAR model (see Ravenna, 2007 as well as Chari *et al.*, 2008).[17] Lag truncation might jeopardize our attempt to identify the "true" technology shock, i.e. the point in time when technology diffusion is triggered or when its future adoption is announced.

The Granger-causality tests displayed in table 2 support our approach: whereas lags of up to 4 quarters of output, investment and TFP Granger-cause standardization, the reverse does not hold. Standards Granger-cause output and investment when 8 lags or more are included and TFP is Granger-caused by standards when 12 lags are used.

We use a Bayesian approach as it allows us to cope with overparameterization while still fully exploiting the information contained in longer lags of our technology variable. In order to deal with overparameterization, we use Bayesian shrinkage where the amount of shrinkage depends positively on the lag number. The Bayesian approach enables us to allow

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[17]A finite order VAR, i.e. a VAR with a truncated lag structure, assumes that lags which are longer than the chosen lag length are zero. However, whenever there is slow diffusion and thus longer lags are non-zero, overly restrictive lag truncation leads to biased estimated coefficients. The true data-generating process is not well represented by a VAR with short lags. As a consequence, the estimated propagation matrix which defines the IRFs is biased despite the identification strategy being correct. Fève and Jidoud (2012) show that the inclusion of many lags considerably reduces the bias in VARs with news shocks. A similar point is raised by Sims (2012) who shows that the bias from non-fundamentalness increases with the anticipation lag of news shocks.

for a differentiated lag structure among the variables in the VAR. The Minnesota prior, which we are using, assumes that own lags are more informative and that longer lags are less relevant. However, we impose a non-decaying prior variance for standards to capture slow diffusion. By not shrinking the influence of long lags of standards, we fully exploit the available information and "let the data speak" as much as possible. We nevertheless avoid an overparameterization of the model as all other variables' lags are shrunk.

We impose a Minnesota prior, i.e. the prior coefficient matrix for macroeconomic variables mimics their unit root properties and the one for technology adoption assumes a white noise behaviour. The prior coefficients are:

$$a_{ijl} = \begin{cases} \delta_i & \text{if } i = j \text{ and } l = 1 \\ 0 & \text{otherwise} \end{cases}$$

The parameter δ_i is set to 1 for non-stationary variables and to zero for stationary variables. All equations are treated symmetrically (Kadiyala and Karlsson, 1997; Sims and Zha, 1998) which implies that the same lag decay for each variable is imposed on all equations. Denoting the prior coefficient with a_{ijl}, the informativeness of the prior is therefore set as follows:

$$V\left(a_{ijl}\right) = \begin{cases} \dfrac{\phi_1}{l^{\phi_4}} & \text{for} \quad i = j, \ l = 1, \dots, p \text{ (own lags, except standards)} \\ \dfrac{\phi_1 \phi_2}{l^{\phi_{4,j}}} \dfrac{\psi_i}{\psi_j} & \text{for} \quad i \neq j, \ l = 1, \dots, p \text{ (lags of other variables)} \\ \phi_3 \psi_i & \text{for the constant} \end{cases}$$

The vector $\phi = (\phi_1 \ \phi_2 \ \phi_3 \ \phi_4)$ denotes the hyperparameters which govern the "tightness" of the prior. Note that, contrary to common set-ups, the lag decay governed by $\phi_{4,j}$ is variable-specific. We assume a quadratic decay of lag importance as is common in the literature and thus set $\phi_{4,j} = 2$ for all j except standards. However, we do not shrink distant lags to zero. Thus, if standards are denoted by the subscript s, $\phi_{4,s} = 0$. The prior on the constant is assumed to be uninformative. Since the implementation of a Normal-Wishart prior requires a symmetric treatment of all equations (Kadiyala and Karlsson, 1997; Sims and Zha, 1998), the hyperparameter ϕ_2 has to be set to 1. The scale parameters ψ_i are commonly set to the standard deviation of a univariate $AR(p)$ regression or can be estimated from the data with the procedure described below.

The parameter ϕ_1 controls the overall shrinkage of the system. When $\phi_1 = 0$, the posterior distribution tends towards the prior distribution and the data are not allowed to "speak"; on the contrary, when $\phi_1 = \infty$, the prior is flat and the posterior estimates coincide with the OLS estimates. In setting ϕ_1, we follow Canova (2007); Giannone *et al.* (2012b) and Carriero *et al.* (2011) and maximize the marginal likelihood of the data with respect to ϕ_1. The marginal likelihood is given by

$$p(Y) = \int \int p(Y \mid \beta, \Sigma) \, p(\beta \mid \Sigma) \, p(\Sigma) \, d\beta \, d\Sigma$$

and is a function of ϕ_1. The marginal likelihood integrates out the uncertainty of the parameters of the model. When we have no a priori information on the hyperparameters, the maximization of $p(Y)$ also leads to a maximization of the posterior of the hyperparameters and is thus equivalent to an Empirical Bayes method (Canova, 2007; Giannone *et al.*,

2012b). We then choose the overall shrinkage parameter ϕ_1 such that

$$\phi_1^* = \arg \max_{\phi_1} \ln p(Y)$$

The appendix describes the prior distributions and the selection of the hyperparameters in more detail.

The original Minnesota prior assumes that the variance-covariance matrix of residuals is diagonal. This assumption might be appropriate for forecasting exercises based on reduced-form VARs, but runs counter to the standard set-up of structural VARs (Kadiyala and Karlsson, 1997). Moreover, impulse response analysis requires the computation of non-linear functions of the estimated coefficients. Thus, despite the fact that analytical results for the posterior of the Minnesota prior are available, numerical simulations have to be used.[18] Every draw of the matrix which maps the reduced-form innovations into structural shocks is taken from the draws of the posterior distribution of the model parameters; the identifying assumptions therefore reflect parameter uncertainty. Hence, we implement a Normal-Wishart prior where the prior mean and variance is specified as in the original Minnesota prior and we simulate the posterior using the Gibbs sampler. More specifically, the prior is implemented by adding dummy observations to the system of VAR equations. The weight of each of the dummies corresponds to the respective prior variance.

5.2   Identification of shocks

When using a direct indicator of technological diffusion, it is important to specify what actually constitutes a technology shock. In the context of this paper, a technology shock is directly concerned with technological change, i.e. it is a shock to the distance between the technology frontier and currently adopted technology which manifests itself by an increase in technological standardization.

A technology shock in the context of this paper is defined as a discrete catch-up with the technology frontier. This frontier is in turn a function of past investment in R&D and patenting (which are by themselves functions of the cycle) and a random science flow. The decision to select one of the existing technologies for standardization and thus commercialization is on the one hand determined by the cycle and on the other hand determined by the distance to the technology frontier. This distance is (partly) exogenous and can provoke a technology shock: whenever a very promising technology emerges, agents will want to standardize beyond of what the cycle would predict in the absence of this technology.

We have direct access to an indicator of technology adoption and thus want to exploit this data without imposing how technology shocks affect certain variables in the long-run, but rather let the data speak. Moreover, by avoiding to rely on long-run restrictions, we assure that we are not confounding technology shocks with any other shocks that have a

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[18]For structural VAR analysis, two approaches are commonly used (Canova, 2007): (1) A prior is imposed on the reduced-form coefficients and augmented by a Normal-Wishart prior whenever the VAR is exactly identified as in the case of Cholesky decomposition. (2) Whenever there is over-identification, Sims and Zha (1998) propose putting a prior on the structural coefficients directly. Restrictions on the structural parameters are also provided by the algorithm developed by Waggoner and Zha (2003).

permanent effect on macroeconomic variables. It is for this reason that we use a Cholesky identification scheme which imposes minimal assumptions on the contemporaneous impact of shocks. Since standardization is the first step of the actual implementation of a new technology which triggers a slow diffusion process, we order standards last in our VAR assuming that a technology shock, i.e. a shock to the distance between currently adopted technologies and the technology frontier, only affects standardization contemporaneously.

In order to analyze the response of standardization to the business cycle, we investigate its reaction to a "business cycle shock". This identification strategy follows Giannone *et al.* (2012a). A business cycle shock is defined as a linear combination of all the shocks in the VAR system which can explain the largest part of the variation of output at business cycle frequencies. This procedure is agnostic about the actual drivers of the business cycle shock which comprises underlying demand and supply side shocks. Nevertheless, it perfectly serves our purpose of identifying a shock which allows us to trace out the reaction of technology adoption to the cycle. Similar procedures using forecast error variance decompositions have been used by Barsky and Sims (2011) and Uhlig (2004). In particular, our "business cycle shock" is derived using frequency domain analysis and its detailed derivation is described in the appendix. We identify the business cycle and technology shocks simultaneously.

6   Discussion of results

In the baseline model, our VAR system is composed of four variables: output in the business sector, non-residential investment in equipment and software, total factor productivity (in the investment sector) which is adjusted for capacity utilization and finally standard counts from the ICT sector. We take investment in equipment and software instead of aggregate non-residential investment (which comprises investment in structures) in order to capture the effect of the implementation of new vintages of capital (which should be largely unrelated to structures). For the estimations, all data are in log levels and collected at a quarterly frequency for the time period 1975Q1–2010Q2.

6.1   Endogenous technology adoption

Empirical evidence has shown that R&D is procyclical on the aggregate (Barlevy, 2007; Ouyang, 2011; Aghion *et al.*, 2012) as is patenting (Griliches, 1990). Our emphasis, however, lies on the analysis of the actual *implementation* of new technologies which is why we want to explore the reaction of standardization to cyclical movements in aggregate macroeconomic variables. Figure 6 displays the responses of standards to a business cycle shock. Figure 6 shows that technology *adoption* is also cycle-driven: the response of standardization to a business cycle shock is positive and significant in the medium-run and peaks around 10 quarters. The cross-correlation pattern shown in figure 5 above can thus be rightly interpreted as being (partly) driven by causality running from the cycle to technology adoption.

Our results are in line with the evidence presented in Geroski and Walters (1995) who show that technologies are adopted in clusters which coincide with economic booms. Procyclicality can mainly arise due to two effects. *First*, firms might prefer to adopt technologies during economic upturns if they aim to maximize their profits when demand

is high. Francois and Lloyd-Ellis (2003) build a theoretical model which relies on the endogenous clustering of technology implementation as entrepreneurs seek to delay adoption until the time of an economic boom in order to realize high rents. Shleifer (1986) shows how firms prefer to introduce new technologies in booms because profits from innovation are transitory due to imitation by competitors. *Second*, the process of standardization does not come without cost as firms need to invest into the adoption of new technologies, replace old standards and potentially increase human capital effort. Costs also accrue to users (manufacturers and service providers) and final consumers. For instance, Jovanovic (1995) shows that the costs for the implementation of new technologies outnumber the research costs by a factor of 20. Credit constrained firms could thus find it difficult to finance these costly investments in economic downturns. The decision to standardize is ultimately a costly decision to catch-up with an ever-evolving technology frontier. Standardization is thus not only a positive function of the distance to this frontier, but also a positive function of the cycle whenever firms are financially constrained or want to capitalize on their costly investment in new technologies by profiting from higher demand.

According to our finding, the procyclical time series patterns in figures 4 and 5 are not, or not only, due to technology driving the cycle (as the RBC conjecture predicts), but causality actually also runs from the cycle to technology. In much of the macroeconomic literature, scientific innovations are assumed to appear randomly from nowhere (which is already a strong simplification given procyclical R&D and patenting); however, the results point to technology adoption, and thus ultimately productivity, being a function of macroeconomic conditions. This finding seriously challenges the idea of technology being exogenous.

The forecast error variance decompositions at different frequencies are displayed in table 4 and figure 8. The results show that the business cycle shock mainly influences standardization at low frequencies. The very high frequency variation which characterizes the standards series is to a large extent generated by idiosyncratic movements. Macroeconomic shocks rather play a role for overall trends in technology adoption, but cannot account for the spikes in the standard series which result from the fact that technology adoption is by its very nature a lumpy decision. Our results relate to those of Comin and Gertler (2006) who show that, at the medium-term cycle (defined as the frequencies between 2–200 quarters), embodied technological change is procyclical.

6.2   Transitory dynamics following a technology shock

How does the cycle react to a technology shock?

Most obviously, we investigate what are the aggregate effects of technology shocks on the macroeconomic cycle. We will first discuss the reaction of output and investment before turning to TFP further below. Figure 7 displays the impulse responses to a technology shock. The reaction of output is positive and displays an S-shaped initial response as does investment. For both output and investment, the reaction is sluggish immediately after the shock, picks up after 4–6 quarters and reaches its maximum after 10–12 quarters. The effect of the identified technology shock is permanent. This shape is indicative of typical processes of technology diffusion (Griliches, 1957; Jovanovic and Lach, 1989; Lippi and Reichlin, 1994). Different technologies diffuse at different speed with estimates of adoption

lags ranging from a few years to several decades with more recent innovations adopted faster than older ones (Comin and Hobijn, 2010). The effects of the type of technology adoption we measure in our setup materialize fully after 4 years.

Our indicator of investment picks up to what extent the implementation of new technologies is mirrored by an increase of investment in equipment and software. In order to verify the validity of our technology indicator, we explore which sub-components of investment in equipment and software are affected the most. For the purpose of analyzing these sectoral effects, we follow the strategy of Barth and Ramey (2001) and estimate a VAR where the sectoral variable is block-exogenous to the remaining VAR system. This block exogeneity assumption ensures that the estimated VAR coefficients remain the same as in the baseline model and that the technology shock is identified consistently.

The results in table 3 are convincing in that our indicator seems to correctly pick up a technology shock: it is above all investment in computers and peripheral equipment, followed by investment in software, whose reaction outnumbers the one of non-technological equipment by a factor of 4 approximately. Other types of investment react only to a considerably smaller extent than technology-intensive equipment.

Quantitative importance of technology shocks

The early RBC literature attributed a very large share of variations in aggregate fluctuations to "technology shocks". Though the RBC conjecture has been criticized extensively, the hypothesis of technology-driven business cycles has seen a revival with the vintage capital literature and in particular the literature on investment-specific technological (IST) change (Greenwood *et al.*, 1988, 1997). However, evidence on the role of IST shocks for business cycle fluctuations is mixed.[19] Decomposing the variances at different frequencies is instructive for understanding which frequency component of the data is influenced by the shocks. The results are displayed in table 4 for business cycle frequencies and the whole spectrum as well as in figure 8 which graphs the contribution of the business cycle and technology shocks to the fluctuations of the variables of interest at different frequencies.

Business cycle frequencies (8 to 32 quarters). Our identified technology shocks only contribute to a small extent to output or investment in the short-run; the results are more meaningful for TFP. The results of table 4 indicate that the contribution of our identified technology shocks are far from what is sometimes found in the IST literature, let alone the early RBC literature. However, compared to the well defined technology shock that we are identifying, the conceptual interpretation of what constitutes neutral technology or IST shocks is extremely broad.[20] For instance, IST shocks are identified somewhat

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[19]Greenwood *et al.* (2000) find that 30% of business cycle fluctuations can be attributed to IST shocks. Fisher (2006) finds that 42% to 67% of output fluctuations are driven by IST shocks. A similar value of 50% is found by Justiniano *et al.* (2010). On the other hand, Smets and Wouters (2007) find substantially smaller values. Defining investment shocks as the rate at which consumption goods are transformed into investment goods, Justiniano *et al.* (2011) and Schmitt-Grohé and Uribe (2012) find that investment shocks do not contribute to business cycle volatility. However, shocks to the rate at which investment goods are transformed into installed capital are found to be important drivers of business cycles.

[20]Neutral technology shocks are generally accepted as a black box and "measure of our ignorance", but even IST change is interpreted differently in the literature. Whereas one part of the literature clearly

agnostically (similar to neutral technology) which is mirrored in the fact that the IST literature identifies shocks deduced from data on the relative price of investment. Price data, however, should reflect both technological change as well as demand effects or changes in the competitive market structure. It is thus not clear to what extent IST shocks stem from purely technological factors. In this respect, Justiniano *et al.* (2011) show that an identification based solely on data of the relative price of investment will confound several of its determinants of which technological change is just one among many. This paper, on the contrary, identifies a very specific technology shock which is not a black box. We do not claim that other "technology shocks" such as policy changes, organizational restructuring or human capital are equally or even more important for aggregate volatility. However, their propagation might be quite different which is why it is crucial to analyze them separately. The fact that we are isolating a "unique" technology adoption shock which is not a linear combination of several underlying shocks explains the magnitude of the decompositions. The above results are comparable with the ones of Alexopoulos (2011) in terms of the contribution of technology shocks to aggregate volatility.

Medium- and long-term impact. From table 4, and more so from figure 8, it is obvious that technology shocks play a more important role for investment and output at lower frequencies. This result is in line with what one would expect from growth theory. The effect of a technology shock on TFP is both important at business cycle frequencies and in the long-run. The decompositions are consistent with the idea that the introduction of a new technology causes organizational changes in the short- and medium-run on the industry and plant level, but that its aggregate effects on the macroeconomic cycle matter predominantly in the long-term.

A closer look at TFP

We interpret our measure of technology adoption as an indicator of the introduction of new vintages of capital that differ in productivity from older vintages. Technology adoption is therefore a measure of *embodied* technological change. On the contrary, *neutral* technology shocks as represented by TFP are a measure of *disembodied* technological change.

Figure 7 shows that TFP in the investment sector falls below trend following a shock to technology adoption. Even when a technology is adopted by firms, an immediate pick-up of productivity cannot be taken for granted. This finding thus runs counter to RBC-type approaches where technology shocks are assumed to lead to immediate innovations in TFP. On the contrary, it has been shown that labour productivity can slow down following the introduction of a new technology due to the incompatibility of the new technology with the installed base (Farrell and Saloner, 1986). This incompatibility concerns both human and organizational capital as well as physical capital. Standardization has nevertheless an important implication for future technological progress. Innovative applications are built upon standards as a common technological basis: an important investment must be made in *incremental* innovation and in the construction of compatible physical and

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associates IST shocks with technological change (Greenwood *et al.*, 1997, 2000; Fisher, 2006), others interpret IST shocks as demand shocks (Smets and Wouters, 2007) or associate elements of it with financial frictions (Justiniano *et al.*, 2011).

human capital in order to exploit the technological potential of the new *fundamental* technology (the standard). After a radical technology shock, TFP can therefore temporarily decrease, before the implementation and deployment of the new technology raises the level of productivity permanently. Our work can therefore be related to the vintage capital literature which identifies discontinuous technological change as a driver of temporary slowdowns in productivity (Samaniego, 2006; Greenwood and Yorukoglu, 1997; Yorukoglu, 1998).

Our finding casts doubt on macroeconomic models which neglect the microeconomic mechanisms involved with technology adoption and simply assume an immediate pick-up of TFP following the introduction of a new technology. The results also show that TFP is rising in the long-run and thus confirm the productivity-enhancing role of technology adoption and its importance for long-run growth. Interestingly, the response of TFP to a technology shock displays a strikingly similar shape as the reaction of TFP to the news shock identified by Beaudry and Portier (2006).

Explaining TFP is a challenging task as it is essentially an unexplained residual. Our identified technology is not constructed from the innovations of the reduced form VAR and is orthogonal to these. Historical decompositions allow us to assess the quantitative contribution of various shocks over time. Figure 9 displays these decompositions for TFP in the investment sector. The series are simulated by only allowing for technology shocks on the one hand and business cycle shocks on the other hand. Interestingly, the historical decompositions for TFP speak in favour of technology shocks. Though not every spike in TFP can be accounted for by our technology shock, the contribution of technology shocks is quite substantial until the second half of the 1990's and sometimes even outperforms business cycle shocks. This can be interpreted as another important evidence of the role of embodied technological change for disembodied productivity.

6.3   Technological change and anticipation

Figure 7 shows that the effect of technology adoption on the cycle is characterized by slow diffusion. Tangible effects only materialize after several quarters. The propagation of our identified technology shock is therefore comparable to the one of "news shocks". Beaudry and Portier (2006) use stock price movements to identify news about the future and show that these lead to an increase in TFP after several years. These news shocks are interpreted by the authors as news about technological change which only leads to productivity increases after a long process of adoption. Including stock price series into the VAR is not only interesting due to the conceptual similarity of "news shocks" and slow technology diffusion, but is also instructive in order to verify if the above results hold in a system which includes forward-looking variables.

We therefore add the NASDAQ Composite and S&P 500 indices to our VAR. They are ordered last as we assume that news about technology adoption are incorporated by financial markets on impact. Results are displayed in figure 10 which, first of all, shows that the findings from the earlier exercise are not affected by the inclusion of financial market variables. The impulse responses in figure 10 show that both the S&P500 as well as the NASDAQ Composite react positively to a technology adoption shock. More importantly, the reaction of the NASDAQ Composite, which mainly tracks companies in the technology sector, is more pronounced and significant on impact compared to a sluggish response of

the S&P500. The latter is a more general stock market index and might thus not pick up industry-specific information when the shock hits initially. The reaction of the NASDAQ Composite index confirms that financial markets pick up the positive news about future productivity increases despite the initial decline in TFP and the delayed response of output and investment. Our results also compare to the ones of Pástor and Veronesi (2009) who find that technological revolutions can lead to stock market bubbles due to their systematic impact on all firms' future productivity.

7 Extensions

7.1 Variable-specific lag decay

The above analysis relies on the prior assumption that the behaviour of the variables in the VAR system can be well described by the Minnesota prior moments. Compared to common approaches, we propose to introduce a differentiated lag structure in order to *not* shrink the influence of distant lags of our technology indicator (mirrored by the fact that the lag decay parameter $\phi_{4,j} = 2$ for macroeconomic variables and $\phi_{4,j} = 0$ for standards). In the following, we want to verify to what extent this assumption is supported by the data.

For our empirical analysis above, we estimated the overall shrinkage parameter from the data by maximizing the marginal likelihood of the model. Here, we extend this procedure to the lag decay parameter $\phi_{4,j}$ which had been fixed until now. In particular, the lag decay is allowed to differ among variables which is why we denote it with $\phi_{4,i}$. In addition, we follow Giannone *et al.* (2012b) in treating the elements ψ_i of the prior moments of the variance-covariance matrix Ψ as hyperparameters in order to ensure that a maximum of our prior parameters is estimated in a data-driven way.

The vector of hyperparameters Θ which comprises ϕ_1, $\phi_{4,i}$ and all of the ψ_i is estimated from the data as above by maximizing the marginal likelihood:

$$\Theta^* = \arg \max_{\Theta} \ln p(Y)$$

The reader is referred to the appendix for a detailed discussion.

Table 5 displays the estimates of $\phi_{4,i}$. Since this hyperparameter is an exponent, the differences across variables become most apparent when calculating the implied decay directly. The estimates show that the hyperparameters for the macroeconomic variables are at least three times as large as the one for the standard series. Compared to the distant lags of macroeconomic variables, this translates into the shrinkage of the standards lags being considerably smaller. This difference can take on values of up to 30.

The results thus broadly confirm our assumptions from above. The prior variance for distant lags of the standards series is less tight, thus implying that long lags of the standard series are given more weight to influence the estimates than are the lags of the macroeconomic variables. This is consistent with the idea of slow technology diffusion that motivated our econometric approach. Figure 11 shows the impulse responses of the system where all hyperparameters were estimated by maximizing the marginal likelihood of the model. Responses are very similar to the ones in the baseline specification (figure 7) and thus confirm our results from above.

7.2 Larger VAR system

The Bayesian VAR approach allows us to include a large number of variables as the complexity of the system is automatically taken care oft by the adjustment of the hyperparameter ϕ_1. In order to verify the robustness of our results, we estimate a larger VAR system composed of 12 variables: output in the business sector, investment in equipment and software, consumption of goods and services, hours worked in the business sector, capacity utilization, TFP (adjusted for capacity utilization) in the investment goods sector as well as consumption goods sector, the relative price of investment in equipment and software, the federal funds rate, ICT standards and the stock market indices, S&P 500 and NASDAQ Composite. We identify the technology shock as before and restrict the system to only allow for a contemporaneous reaction of standards and the stock market indices in response to a technology shock.

The results are displayed in figure 12. We first note that our results from the previous sections also hold in the larger system. Figure 12 shows that the identified technology shocks produce comovement of output, hours, consumption and investment. In standard macroeconomic models where shocks trigger technological diffusion, wealth effects should lead to a decline in hours worked, investment and output as agents shift towards more consumption in the prospect of higher future productivity (Cochrane, 1994). However, if adoption is costly and requires training, a rise in labour *demand* reverses the effect on hours worked and investment since it requires more labour input and physical investment to implement new technologies whose higher productivity only materializes after several quarters. Regarding the *supply* of labour, the response of hours worked might be due to the fact that wealth effects on labour supply are actually nil or very small for the case of technology shocks (as would be the case when Greenwood-Hercowitz-Huffman (GHH) preferences prevail). At least in the short-run, this seems a plausible explanation as the introduction of new technologies is nevertheless associated with a lot of uncertainty regarding the timing and magnitude of future productivity improvements; intertemporal substitution effects might thus play a smaller role.

The results in figure 12 also demonstrate that capacity utilization rises until the technology shock has fully materialized. This is in line with the IST shock literature (i.e. Greenwood *et al.*, 2000) where an IST shock leads to a higher rate of utilization of existing capital: the marginal utilization cost of installed capital is lowered when its relative value decreases in the light of technologically improved new vintages of capital. Once technology has fully diffused (output, investment and consumption are at a permanently higher level), capacity utilization and hours decline again. The relative price of investment decreases following a technology shock but only does so after several years. The effect of a technology shock on the Federal Funds rate is nil.

7.3 Different standard measures

In the above analysis, we used standard counts from ICS class 33 (Telecommunications) and 35 (Information technologies) which are issued by US American standard setting organizations. As a robustness check, we add standards from international standard setting organizations which apply as well to the US. As another robustness check, we add electronics to our measure of standards as it might also capture a sector in which

general purpose technologies have been invented and adopted. We therefore not only collect ICT standards (ICS classes 33 and 35), but also collect data for a composite indicator which comprises: Electronics (31), Telecommunications/Audio and video engineering (33), Information technology/Office machines (35) and Image technology (37). We construct a measure of these ICS classes both from US standard setting organizations as well as one that additionally includes international standard setters.

The results of this robustness check are displayed in figure 13: we display the impulses responses using our original measure (ICS classes 33–35), but also add the larger definition of ICT standards (ICS classes 31–37) as well as the respective series corresponding to the sum of standards released by US and international standard setting organizations. The responses to technology shocks identified from the different indicators behave very similarly and thus confirm our results from above: output and investment rise permanently after being indicative of S-shaped diffusion patterns, TFP only rises after considerable lags, hours worked and capacity utilization rise temporarily, the relative price of investment declines in the long-run and stock markets pick up the shock on impact and react positively.

We also run VAR specifications using standard counts from other sectors such as manufacturing and services or using the aggregate number of standards released per quarter (results not shown). Though the responses of macroeconomic variables to a "technology shock" (same identification as when using ICT standards) are qualitatively similar, they are often insignificant and less pronounced. Not only does this finding confirm that our indicator of technological diffusion is not completely random, it also highlights the extent to which ICT has served as a general purpose technology and has contributed to higher productivity and output in the last decades.

8 Conclusion

This paper seeks not only to answer the ever rebounding question of the role of technology shocks in macroeconomics, but explicitly tries to explain technology as a phenomenon itself. By identifying an important microeconomic indicator which is grounded in innovation economics, namely technological standardization, we are able to investigate the interaction between the macroeconomic cycle and technology.

Business cycle theories generally rely on exogenous processes for technology. In these models, positive shocks translate into movements of macroeconomic variables on impact, in particular to immediate increases in TFP. Though the short-cut of exogenous productivity might be admissible in some frameworks, it bears the risk of leading to incorrect conclusions in a large number of settings. In this paper, we draw a picture that is more in line with the microeconomic concept of technology: adoption rates are procyclical, technology diffuses slowly and its effects only materialize after considerable delay. The feedback between the cycle and technology is circular, but not instantaneous.

Addressing the question of the exogeneity and stochastic nature of technology, we find that technology, especially in terms of adoption rather than invention, is both a determinant as well as a result of macroeconomic fluctuations. Mechanisms such as demand effects and financing constraints make technology a function of the cycle and therefore highlight the important dynamics that characterize this interplay.

We show that our identified technology shock generates an S-shaped response of output and investment as is typical of technological diffusion. Regarding the transitory dynamics of shocks to embodied technological change, we show that technology leads to an increase in productivity in the long-run, but the very nature of radical and discontinuous technology can cause TFP to decrease in the short-run. We can therefore reconcile the fact that productivity slowdowns are observed in the data with the notion of a technology frontier which nevertheless increases constantly. The results of this paper show that a clear distinction between embodied technology, radical technical change and disembodied technology is needed in order to better understand productivity which is essentially a multifaceted phenomenon.

Our results also help to gain insights about the nature of shocks such as the ones found in the "news shock" literature which are often assumed to appear out of nowhere and are hardly given a structural interpretation. Slow technological diffusion is characterized by similar propagation dynamics due to anticipation effects. In particular, the initial decision to adopt a new technology leads to lagged responses of macroeconomic variables. This paper shows that standardization is a trigger of technological diffusion and acts as a signaling device which informs agents about future macroeconomic developments. It is for this reason that forward-looking variables such as stock market indices, and in particular the NASDAQ Composite index which tracks high-tech companies, react to a technology shock on impact.

Overall, this paper stresses the importance of looking into the microeconomic mechanisms that are at the basis of the driving forces of macroeconomic fluctuations. Using the insights from the literature on industrial organization and innovation should help macroeconomists in opening the black box which makes up technology and productivity. Understanding the different dimensions of technological progress and disembodied productivity is ultimately a necessary condition for uncovering the different channels which impede and foster economic growth.

Appendix

A.   Identification of a business cycle shock using frequency domain analysis

A business cycle shock is identified as in Giannone *et al.* (2012a) which adapts the identification strategy of DiCecio and Owyang (2010). This appendix largely follows the notation of Altig *et al.* (2005) who analyze the quantitative impact of various shocks on the cyclical properties of macroeconomic variables. Starting from a reduced form VAR model

$$Y_t = A(L)Y_t + u_t \quad \text{where} \quad E[u_t u_t'] = \Sigma$$

it is straightforward to derive its structural representation:

$$
\begin{aligned}
B_0 Y_t &= B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + B_p Y_{t-p} + \varepsilon_t \\
Y_t &= (B_0)^{-1} B(L) Y_t + (B_0)^{-1} \varepsilon_t \\
&= A(L)Y_t + u_t && \text{where} \quad A(L) = (B_0)^{-1} B(L) \quad \text{and} \quad u_t = (B_0)^{-1} \varepsilon_t \\
&= [I - A(L)]^{-1} CC^{-1} u_t && \text{where} \quad C = (B_0)^{-1} \\
&= [I - A(L)]^{-1} C \varepsilon_t && \text{where} \quad \varepsilon_t = C^{-1} u_t \quad \text{and} \quad E[\varepsilon_t \varepsilon_t'] = B_0 \Sigma B_0' = I
\end{aligned}
$$

The matrix B_0 maps the reduced-form shocks into their structural counterparts. Identification of the structural shocks can be achieved using various strategies such as short-run and long-run restrictions. Assuming a Cholesky identification, the variance-covariance matrix of residuals of the reduced form VAR, Σ, can be decomposed in order to restrict the matrix C:

$$\Sigma = CC' \quad \text{and} \quad C = \text{chol}(\Sigma)$$

The identification of a business cycle shock is achieved by extracting a shock process which is a linear combination of all the shocks in the VAR system (except the technology shock) that leads to a high variation in output at business cycle frequencies. However, the identification of the technology shock, the column corresponding to the standardization variable, is left unchanged and identified via the standard Cholesky approach. In order to achieve the simultaneous identification of the technology and the "business cycle shock", a set of column vectors of C is rotated so that the shock $\varepsilon_{j,t}$ maximizes the forecast error variance of one of the variables $Y_{k,t}$ of the vector Y_t at business cycle frequencies. In the present case, the variable $Y_{k,t}$ corresponds to output. We denote the rotation matrix by R and can re-write our structural VAR accordingly:

$$Y_t = [I - A(L)]^{-1} CRR^{-1}C^{-1} u_t = [I - A(L)]^{-1} CR\varepsilon_t^* \quad \text{where} \quad \varepsilon_t^* = R^{-1}C^{-1} u_t$$

The variance of Y_t can be defined in the time domain:

$$E[Y_t Y_t'] = [I - A(L)]^{-1} CRR'C' [I - A(L)']^{-1}$$

Deriving its equivalent representation in the frequency domain requires the use of spectral densities. The spectral density of the vector Y_t is given by:

$$S_Y(e^{-i\omega}) = \left[I - A(e^{-i\omega})\right]^{-1} CRR'C' \left[I - A(e^{-i\omega})'\right]^{-1}$$

The spectral density due to shock $\varepsilon_{t,j}$ is equivalently:

$$S_{Y,j}(e^{-i\omega}) = \left[I - A(e^{-i\omega})\right]^{-1} CRI_jR'C' \left[I - A(e^{-i\omega})'\right]^{-1}$$

where I_j is a square matrix of zeros with dimension equal to the number of variables and the j-th diagonal element equal to unity. The term $A(e^{-i\omega})'$ denotes the transpose of the conjugate of $A(e^{-i\omega})$. We are interested in the share of the forecast error variance of variable $Y_{k,t}$ which can be explained by shock $\varepsilon_{t,j}$. The respective variances are restricted to a certain frequency range $[a, b]$. The ratio of variances to be maximized is then:

$$V_{k,j} = \iota_k' \frac{\int_a^b S_{Y,j}(e^{-i\omega})d\omega}{\int_a^b S_Y(e^{-i\omega})d\omega} \iota_k$$

where ι_k is a selection vector of zeros and the k-th element equal to unity. For business cycle frequencies with quarterly data, the frequency range $a = \frac{2\pi}{32}$ and $b = \frac{2\pi}{8}$ is used. The integral can be approximated by

$$\frac{1}{2\pi} \int_{-\pi}^{\pi} S(e^{-i\omega})d\omega \approx \frac{1}{N} \sum_{k=-\frac{N}{2}+1}^{\frac{N}{2}} S(e^{-i\omega_k}) \quad \text{where} \quad \omega_k = \frac{2\pi k}{N}$$

for a large enough value of N. The contribution of shock ε_j to the forecast error variance of variable $Y_{t,k}$ at certain frequencies is consequently determined by:

$$V_{k,j} = \iota_k' \frac{\sum_{k=N/a}^{N/b} S_{Y,j}(e^{-i\omega_k})}{\sum_{k=N/a}^{N/b} S_Y(e^{-i\omega_k})} \iota_k$$

The identification consists of finding the rotation matrix R such that $V_{k,j}$ is maximized.

B. Details on the BVAR with a Normal-Wishart prior

Let us write our reduced-form VAR system as follows:

$$Y_t = X_t A + u_t \quad \text{where} \quad E[u_t u_t'] = \Sigma$$
$$u_t \sim \mathcal{N}(0, \Sigma)$$
$$\text{vec}(u_t) \sim \mathcal{N}(0, \Sigma \otimes I_{T-p})$$

X_t comprises the lagged variables of the VAR system and A denotes the coefficient matrix. The Normal-Wishart conjugate prior assumes the following moments:

$$\Sigma \sim \mathcal{IW}(\Psi, d)$$
$$\text{vec}(A) \mid \Sigma \sim \mathcal{N}(b, \Sigma \otimes \Omega)$$

The literature has usually set the diagonal elements of Ψ, ψ_i, proportional to the variance of the residuals of a univariate $AR(p)$ regression: $\psi_i = \sigma_i^2(d - k - 1)$ where k denotes the number of variables. This ensures that $E(\Psi) = \text{diag}(\sigma_1^2, \ldots \sigma_k^2)$ which approximates the Minnesota prior variance. Here, however, we follow Giannone *et al.* (2012b) in treating the diagonal elements of Ψ as hyperparameters in order to ensure that a maximum of our

prior parameters is estimated in a data-driven way. For the Wishart prior to be proper, the degrees of freedom parameter, d, must be at least $k + 2$ which is why we set $d = k + 2$.

This paper generalizes the Minnesota approach by allowing for a variable-specific lag decay. Since ϕ_4 varies by each variable, we denote it by $\phi_{4,i}$. It can be shown that a Minnesota prior structure with variable-specific lag decay is imposed if the diagonal elements of Ω are set to $(d - k - 1)\phi_1/(l^{\phi_{4,j}}\psi_j)$. As a result, the prior structure writes as follows:

$$a_{ijl} \mid \Sigma \sim \mathcal{N}\left(\alpha_{ijs}, \frac{\phi_1}{l^{\phi_{4,j}}}\frac{\psi_i}{\psi_j}\right) \quad \text{with} \quad \alpha_{ijl} = \left\{ \begin{array}{ll} \delta_i & \text{if } i = j \text{ and } l = 1 \\ 0 & \text{otherwise} \end{array} \right.$$

The above expression shows that the Normal-Wishart prior maps into a Minnesota design with the particularity of ϕ_2 being equal to one and ϕ_4 being variable-specific. We have to impose $\phi_2 = 1$ due to the Kronecker structure of the variance-covariance matrix of the prior distribution which imposes that all equations are treated symmetrically; they can only differ by the scale parameter implied by Σ (see Kadiyala and Karlsson, 1997; Sims and Zha, 1998). As a corollary, the lag decay parameter $\phi_{4,j}$ can be specific to variable j, but cannot differ by equation i.

Since the prior parameters β, Ω, Ψ and d are set in a way that they coincide with the moments implied by the Minnesota prior, they thus depend on a set of hyperparameters Θ which comprises ϕ_1, $\phi_{4,i}$ and ψ_i (ϕ_2 and ϕ_3 are fixed). Integrating out the uncertainty of the parameters of the model, the marginal likelihood conditions on the hyperparameters Θ that define the prior moments. Maximizing the marginal likelihood with respect to Θ is equivalent to an Empirical Bayes method where parameters of the prior distribution are estimated from the data. The marginal likelihood is given by

$$p(Y) = \int\int p(Y \mid \beta, \Sigma)\,p(\beta \mid \Sigma)\,p(\Sigma)\,d\beta\,d\Sigma$$

and analytical solutions are available for the Normal-Wishart family of prior distributions (see Giannone *et al.*, 2012b for an expression and a detailed derivation).

Maximizing the marginal likelihood (or its logarithm) yields the optimal vector of hyperparameters:

$$\Theta^* = \arg\max_{\Theta} \ln p(Y)$$

Giannone *et al.* (2012b) adopt a more flexible approach by placing a prior structure on the hyperparameters. The above procedure is thus equivalent to imposing a flat hyperprior on the model.

C. Data sources

Variable	Description	Source	Details
Standards	Number of standards released by American standard setting organizations (ICS classes 33 and 35)	PERINORM database	
Patents	Number of patents applied for in the US (PATSTAT categories G and H as well as USPTO's category 2)	PATSTAT database, US Patent and Trademark Office (USPTO)	
Output	Output in business sector (BLS ID: PRS84006043)	Bureau of Labor Statistics (BLS)	Index (2005=100), seasonal and per capita adjustment
Industrial production indices	Computer and peripheral equipment (NAICS = 3341)	Federal Reserve Board	Index (2007=100), seasonal and per capita adjustment
	Communications equipment (NAICS = 3342)		
	Computers, communications eq., and semiconductors (NAICS = 3341,3342,334412–9)		
Investment (Real private fixed investment, nonresidential)	Equipment and software (NIPA table 5.3.3 line 9)	Bureau of Economic Analysis (BEA)	Index (2005=100), seasonal and per capita adjustment
	Information processing equipment and software (NIPA table 5.3.3 line 10)		
	Computers and peripheral equipment (NIPA table 5.3.3 line 11)		
	Software (NIPA table 5.3.3 line 12)		
	Other equipment and software (NIPA table 5.3.3 line 13)		
	Industrial equipment (NIPA table 5.3.3 line 14)		
	Transportation equipment (NIPA table 5.3.3 line 15)		
	Other equipment (NIPA table 5.3.3 line 16)		
Consumption (Real personal consumption)	Consumption expenditures for goods and services (NIPA table 2.3.3 line 1)	Bureau of Economic Analysis (BEA)	Index (2005=100), seasonal and per capita adjustment
Hours	Hours worked in business sector (BLS ID: PRS84006033)	Bureau of Labor Statistics (BLS)	Index (2005=100), seasonal and per capita adjustment
Total factor productivity	Capacity utilization adjusted total factor productivity (based on data from business sector)	John Fernald (San Francisco Fed)	Index (1947 = 100)
	Capacity utilization adjusted total factor productivity in "investment sector" (equipment and consumer durables)		
	Capacity utilization adjusted total factor productivity in "consumption sector" (non-equipment)		
Stock market indices	S&P 500	Datastream	Deflated, per capita adjustment
	NASDAQ Composite Index		
Capacity utilization	Total index of capacity utilization	Federal Reserve Board	Index in percentage, seasonal adjustment

Relative price of investment	Price of investment in equipment and software (NIPA table 5.3.4 line 9) divided by the price index for personal consumption expenditures for non-durable goods (NIPA table 2.3.4 line 8)	Bureau of Economic Analysis (BEA)	Indices (2005=100), Seasonal adjustment
Federal funds rate	Federal fund effective rate	Federal reserve Board	In percent
Population	Civilian noninstitutional population over 16 (BLS ID: LNU00000000Q)	Bureau of Labor Statistics (BLS)	In hundreds of millions
Price deflator	Implicit price deflator of GDP in the business sector (BLS ID: PRS84006143)	Bureau of Labor Statistics (BLS)	Index (2005=100), seasonal adjustment

Tables

Table 1: International classification of standards (ICS)

ICS class	Description
1	Generalities. Terminology. Standardization. Documentation.
3	Services. Company organization, management and quality. Administration. Transport. Sociology.
7	Mathematics. Natural sciences.
11	Health care technology.
13	Environment. Health protection. Safety.
17	Metrology and measurement. Physical phenomena.
19	Testing.
21	Mechanical systems and components for general use.
23	Fluid systems and components for general use.
25	Manufacturing engineering.
27	Energy and heat transfer engineering.
29	Electrical engineering.
31	Electronics.
33	Telecommunications. Audio and video engineering.
35	Information technology. Office machines.
37	Image technology.
39	Precision mechanics. Jewelry.
43	Road vehicles engineering.
45	Railway engineering.
47	Shipbuilding and marine structures.
49	Aircraft and space vehicle engineering.
53	Materials handling equipment.
55	Packaging and distribution of goods.
59	Textile and leather technology.
61	Clothing industry.
65	Agriculture.
67	Food technology.
71	Chemical technology.
73	Mining and minerals.
75	Petroleum and related technologies.
77	Metallurgy.
79	Wood technology.
81	Glass and ceramics industries.
83	Rubber and plastic industries.
85	Paper technology.
87	Paint and colour industries.
91	Construction materials and building.
93	Civil engineering.
95	Military engineering.
97	Domestic and commercial equipment. Entertainment. Sports.
99	(No title)

Source: International Organization for Standards (2005)

Table 2: Granger causality tests (p-values)

Do macro variables Granger-cause standards?			
	4 lags	8 lags	12 lags
Output	0.000	0.004	0.003
Investment	0.004	0.029	0.053
TFP (adj.) I	0.000	0.000	0.001

Do standards Granger-cause macro variables?			
	4 lags	8 lags	12 lags
Output	0.524	0.020	0.059
Investment	0.004	0.000	0.001
TFP (adj.) I	0.099	0.100	0.021

Notes: The table displays the p-values of the Granger causality tests performed for the baseline model. A deterministic time trend is included in all regressions.

Table 3: Impact of a technology shock, in % at horizon 20

Investment series	IRF
Equipment and software	1.62
Information processing equipment and software	2.07
Computers and peripheral equipment	3.62
Software	2.07
Other	0.98
Industrial equipment	0.68
Transportation equipment	1.69
Other equipment	1.00

Notes: The table displays the value of the impulse response function of the identified technology shock in different sectors of investment after 20 quarters. The identified technology shock is exactly the same as the one in the baseline model and its different sectoral effect is estimated by imposing block exogeneity.

Table 4: Variance decompositions at different frequencies

	Business cycle shock		Technology shock	
Frequency (quarters)	8–32	2–200	8–32	2–200
Output	0.67	0.38	0.09	0.20
Investment	0.33	0.24	0.09	0.15
TFP (adj.) I	0.19	0.20	0.16	0.16
Standards	0.16	0.17	0.62	0.65

Notes: The table displays the contribution of the identified business cycle and technology shocks at business cycle frequencies (8–32 quarters) as well as over the entire spectrum (2–200 quarters).

Table 5: Lag decay estimates

Variable	$\phi_{4,i}$	Implied decay at different lags		
		4	8	12
Output	1.2874	6.0	14.5	24.5
Investment	1.8109	12.3	43.2	90.0
TFP I (adj.)	1.3950	6.9	18.2	32.0
Standards	0.4435	1.8	2.5	3.0

Notes: The table displays the estimates of the lag decay parameter and the implied decay at different lag length for the four-variable baseline model.

Figures and graphs

Figure 1: The interaction between the business cycle and technology

Existing indicators:
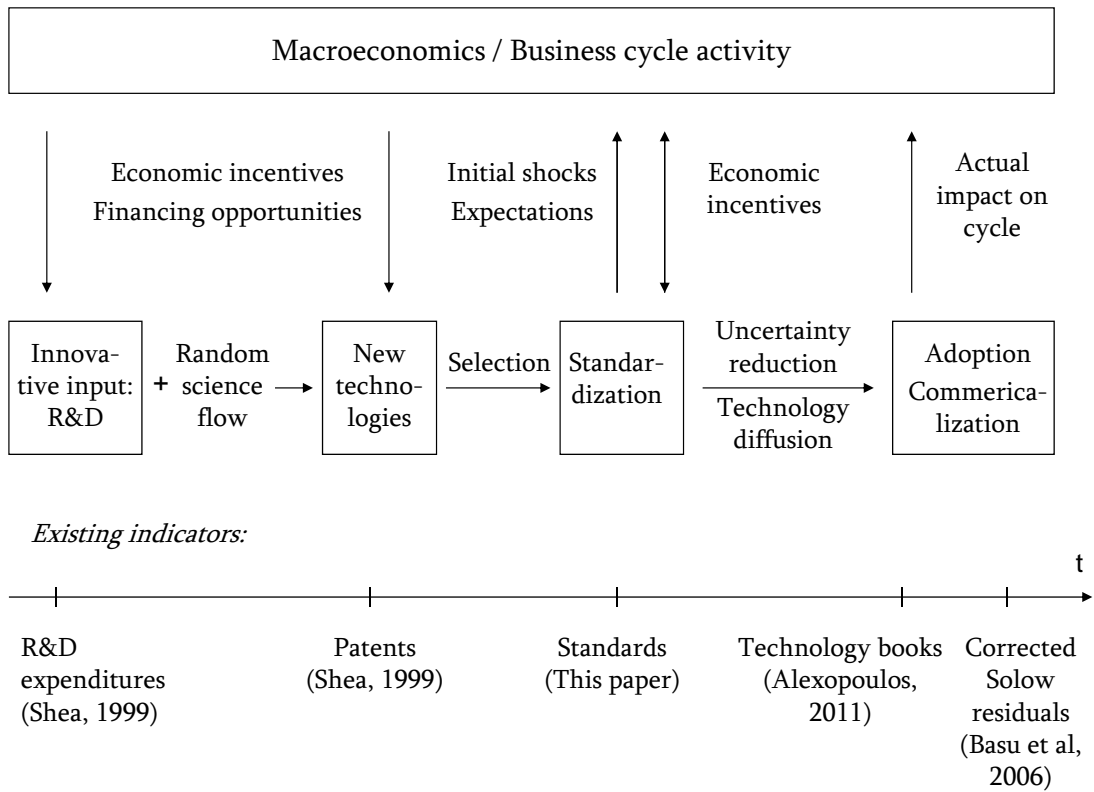
Figure 2: Standard series
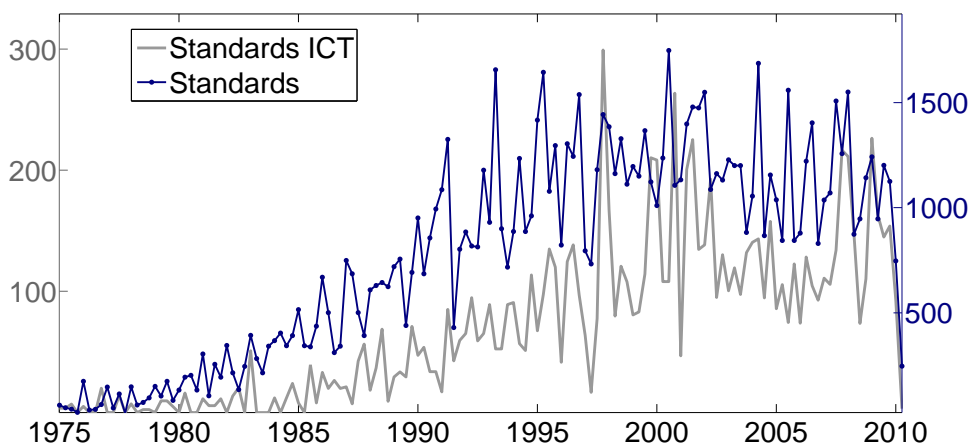
Figure 3: Private R&D expenditures, patent applications and business output
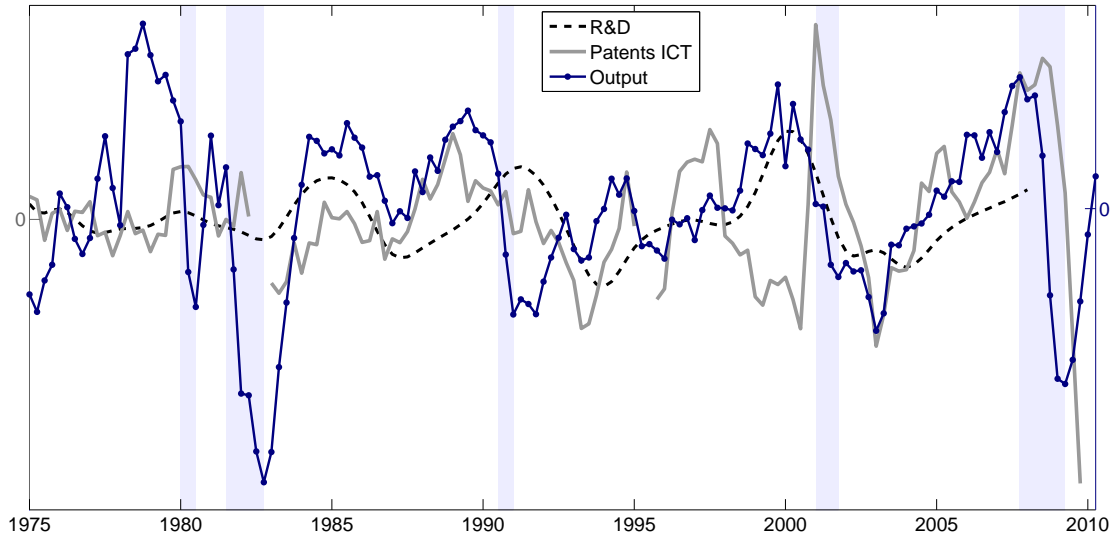
Notes: Data are in logs, seasonally adjusted and HP-detrended (with smoothing parameter 1600). Data for R&D expenditures are only available on an annual basis and therefore interpolated. For the patent series, the data points for 1982Q3–Q4 as well as 1995Q2–Q3 were deleted due to the unusual spikes caused by legal changes in patent law in 1982Q3 and 1995Q2 in order to facilitate the visual comparison.

Figure 4: ICT Standards and business output
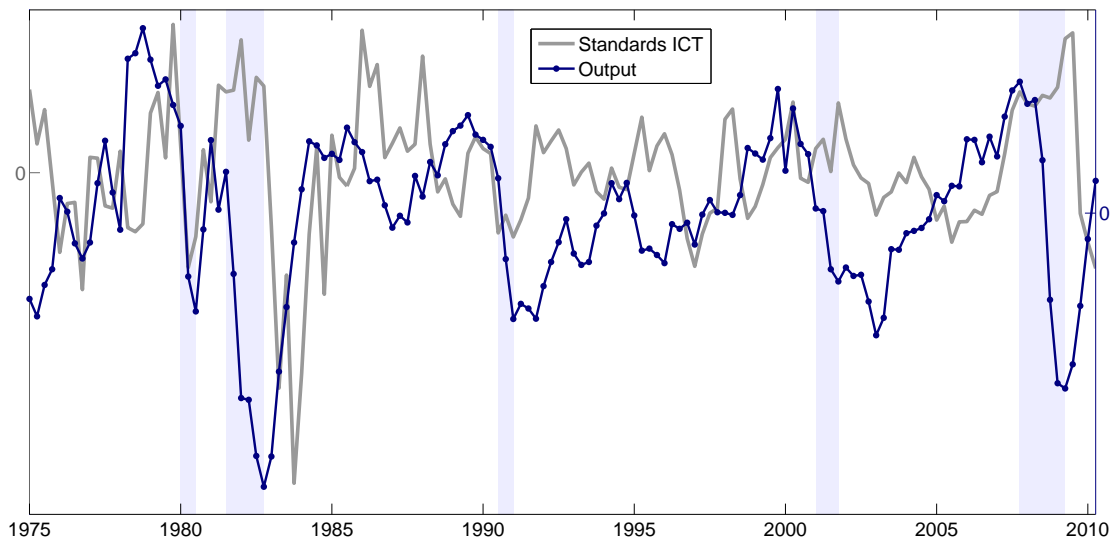
Notes: Data are in logs, and HP-detrended (with smoothing parameter 1600). Output is seasonally adjusted. Standard data are averaged over a centered window of 5 quarters. Shaded areas correspond to NBER recession dates.

Figure 5: Cross-correlations of ICT Standards and macroeconomic variables
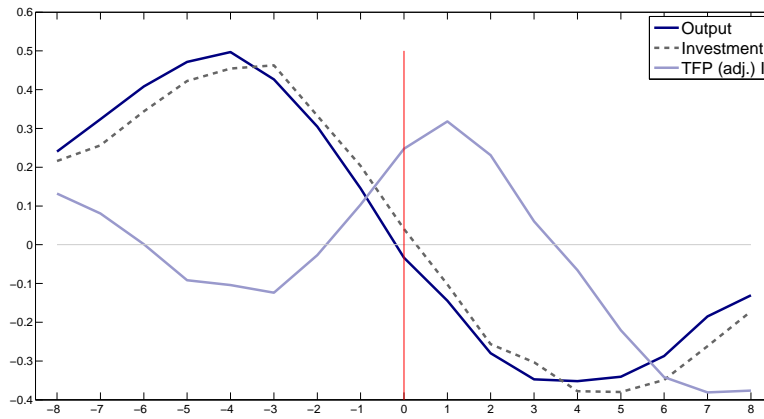
Notes: The x-axis shows quarters and the y axis the estimated cross-correlations. Cross-correlations were calculated based on the data which are in logs, seasonally adjusted and HP-detrended. Standard data are averaged over a centered window of 5 quarters.) The above graph shows that standards are lagging output and investment.

Figure 6: IRFs: Business cycle shock
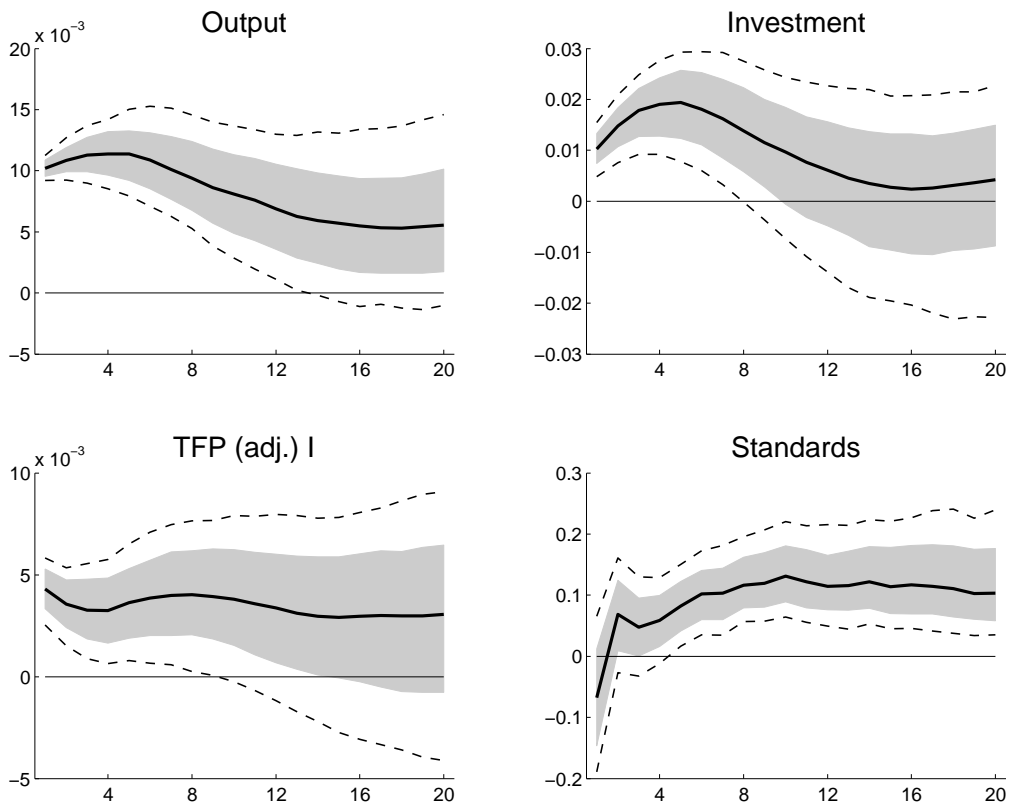
Notes: Impulse responses to a business cycle shock identified as the shock that explains the maximum of the forecast error variance of output at business cycle frequencies (derivation to be found in the appendix). Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively. The unit of the x-axis is quarters.

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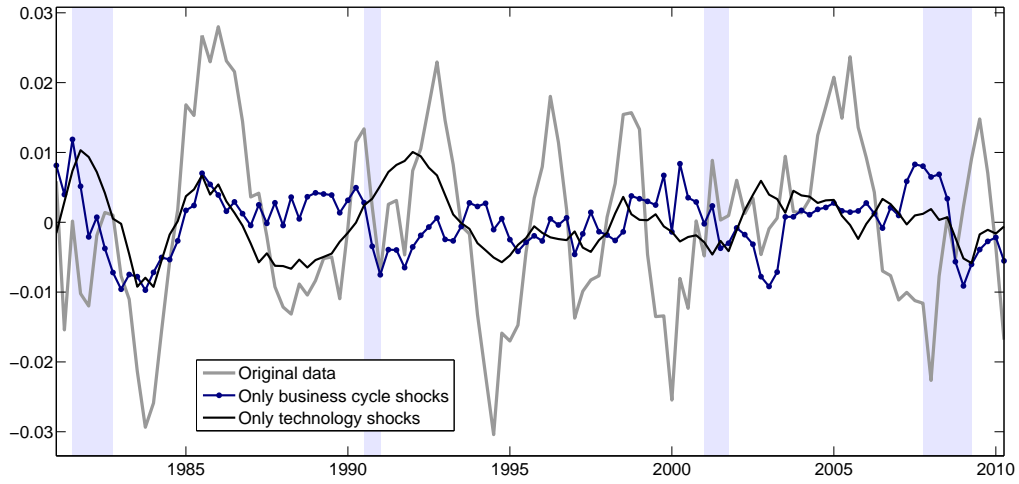Figure 7: IRFs: Responses to a technology shock
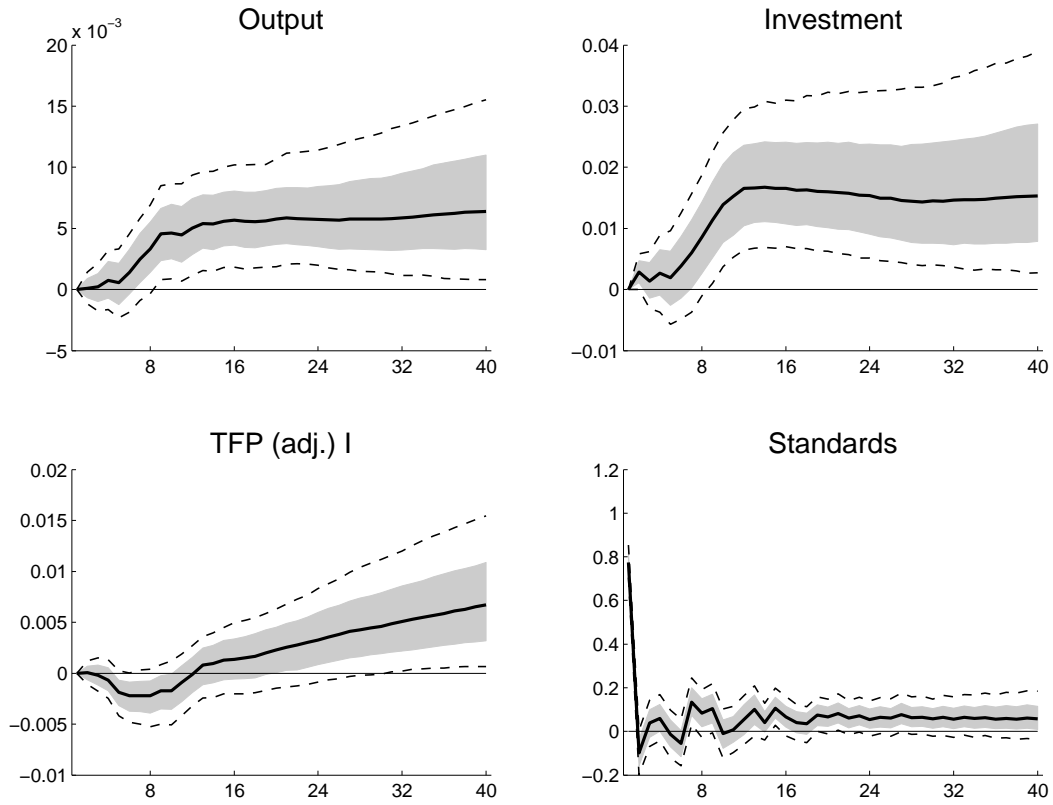
Notes: Impulse responses to a technology shock. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively. The unit of the x-axis is quarters.

Figure 8: Variance decompositions for different frequencies
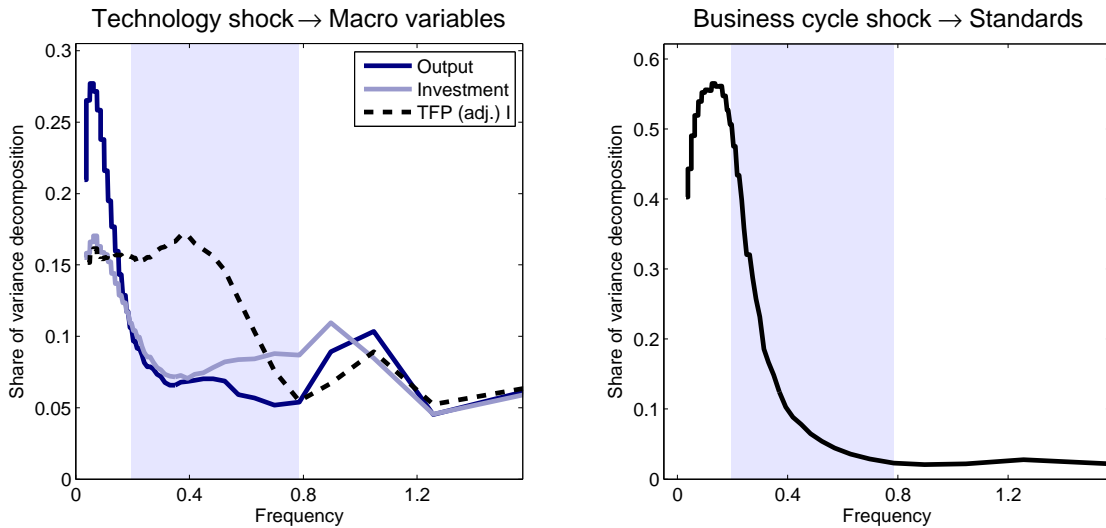
Notes: The variance decompositions refer to the VAR whose impulse response are displayed in figures 6 and 7. The left panel describes the contribution of the identified technology shock to fluctuations of macroeconomic variables and the right panel displays the contribution of the business cycle shock to fluctuations of the standards series. The shaded region corresponds to business cycle frequencies.

Figure 9: Historical decomposition of TFP (adj.)

Notes: The historical decomposition refers to the VAR whose impulse response are displayed in figures 6 and 7. Data are HP-detrended. Standard data are averaged over a centered window of 5 quarters.

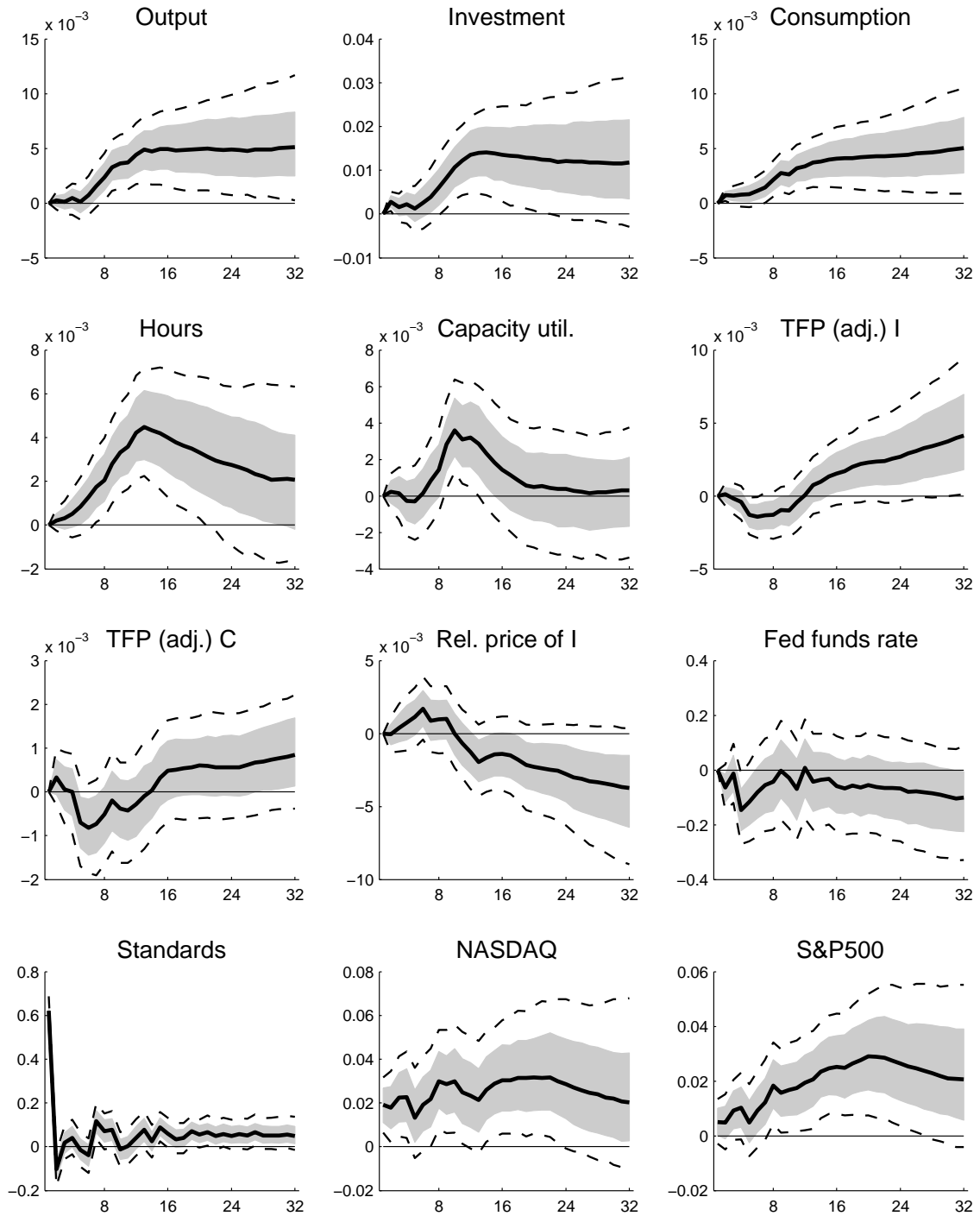Figure 10: IRFs: Responses to a technology shock and news
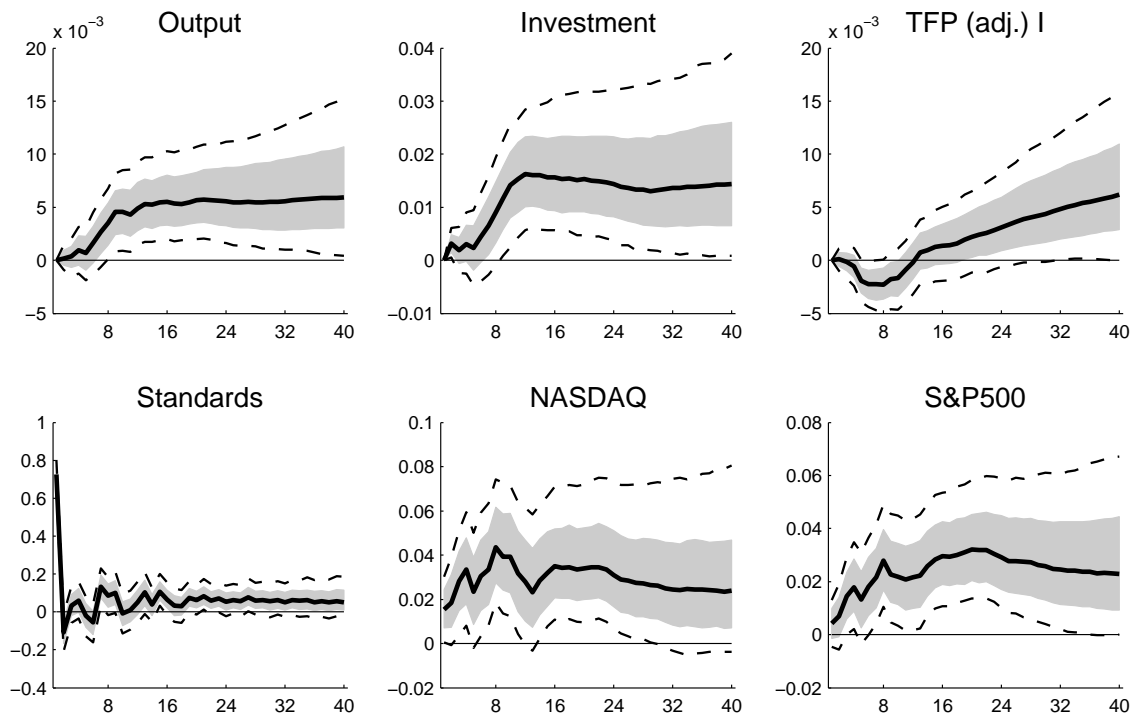
Notes: Impulse responses to a technology shock. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively. The unit of the x-axis is quarters.

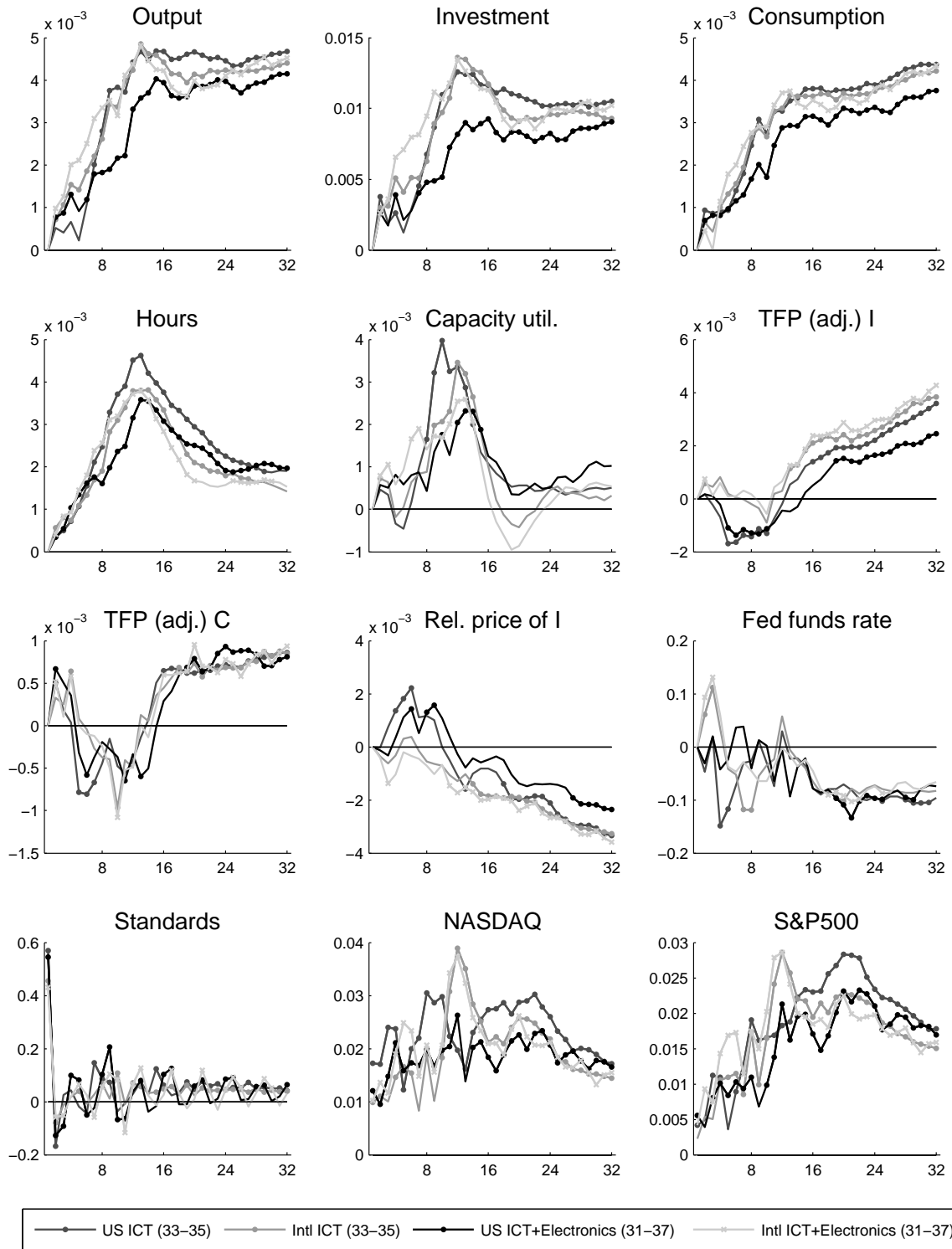Figure 11: IRFs: Responses to a technology shock (data-driven lag decay)
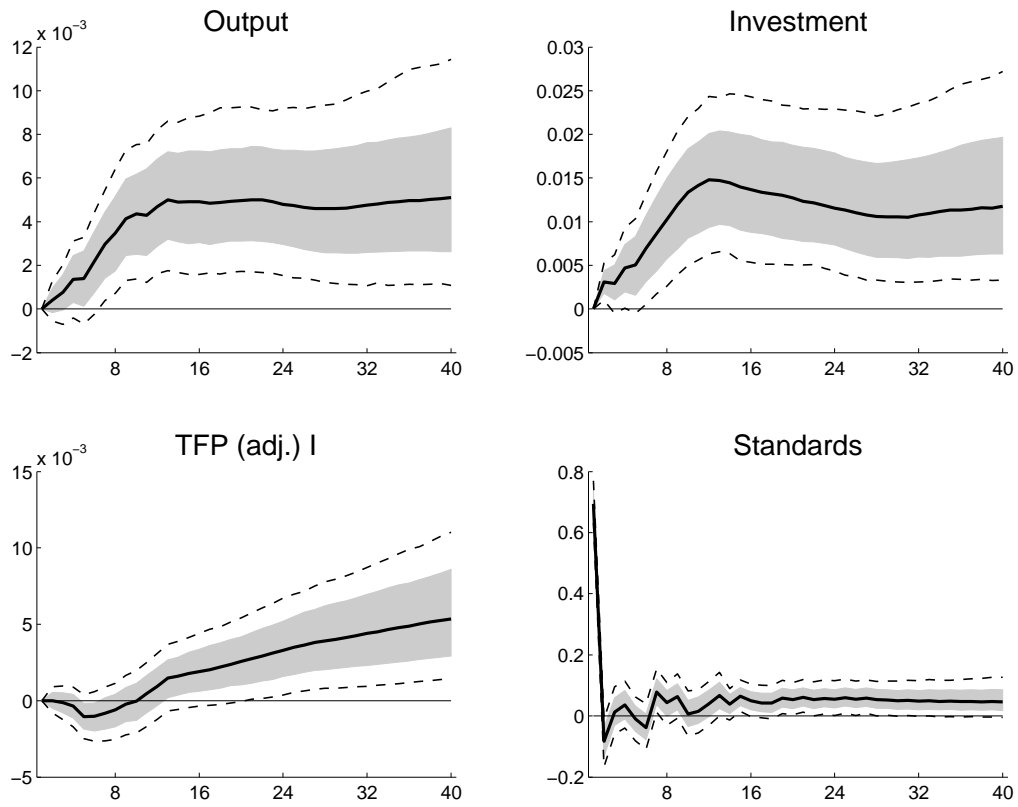
Notes: Impulse responses to a technology shock. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively. The unit of the x-axis is quarters.

Figure 12: IRFs from large system

Notes: Impulse responses to a technology shock. Shaded regions and dotted lines denote 64% and 90% confidence intervals respectively.

Figure 13: IRFs from large system: Different standards measures

Notes: Impulse responses to a technology shock using different standard measures for identification. Circles and crosses denote that the response is significant (one standard deviation confidence bands). The unit of the x-axis is quarters.

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